Master's Thesis

Assessing the Land Cover and Land Use Change and Its Impact on Watershed Services in a Tropical Andean Watershed of Peru

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Abstract

Understanding of land cover and land use change process and its implication for environmental condition and ecosystem functioning, it is essential to identify and recognize the services provided by the ecosystem. Remotely sensed data together with GIS increase the capability to analyze the human impact on the environment in quantitative, qualitative and spatial form. The main goal of this study was to generate the land cover and land use (LCLU) multi-temporal information, to quantify and to analyze the LCLU change and its impact on watershed soil erosion and sediment yield regulation services, and to identify the upstream and downstream relationship on sediment control in Huatanay watershed of Cusco region in the tropical Andes of Peru.

Land cover and land use maps for 1988, 1997 and 2007 were generated and compared statistically through a cross-tabulation obtaining an overall kappa index of: 0.41 for 1988-1997, and 0.40 for 1997-2007, meaning significant changes between the LCLU classes in the studied periods. The LCLU change assessment evaluating area gains and losses and net change in each LCLU class revealed a high dynamic state of the Huatanay watershed landscape, where most of the classes represented changes more than 50% in the studied periods. Most of the LCLU changes were caused by the human action.

The estimated annual average of soil losses in the Huatanay watershed were 319.5, 299.4 and 306.0 ton/ha/year in 1988, 1997 and 2007, which means a slight soil loss declining due to LCLU change (P=0.009). However, more than 50% of the watershed area had soil loss from moderate to extreme, which means that the erosion problem is very relevant in the watershed. The estimated sediment yields in the watershed were 1260.37, 1201.48 and 1227.61 ton/km^2/yr in 1988, 1997 and 2007. The areas of the highest sediment yield values in downstream represent the areas of very active sedimentation process. This is a problem which is getting worse by urban growth in the floodplains, which are important areas for soil deposition. Finally, there was a clear quantitative sediment production and accumulation relationship between the upper and lower parts of the watershed, high sediment production by soil erosion occurring in the middle and upper part and high sediment accumulation occurring in the lower part of the watershed.

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GONZALES INCA, CARLOS A.	Maanpeitteen ja maankäytön muutosten arviointi ja muutosten vaikutus valuma-alueen ekosysteemipalveluihin Perun Andien trooppisella valuma-alueella
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Tiivistelmä

Tutkittaessa maanpeitteen ja maankäytön muutoksia sekä niiden vaikutuksia ympäristön tilaan ja ekosysteemin toimintaan, on oleellista tunnistaa ekosysteemin tarjoamat palvelut. Kaukokartoitus ja paikkatietojärjestelmät lisäävät mahdollisuuksia analysoida ihmisen vaikutusta ympäristöön sijaintitiedot huomioiden sekä määrällisesti että laadullisesti. Tämän tutkimuksen päätavoite oli tuottaa maanpeite- ja maankäyttö (MPMK) -aineistoa eri ajanjaksoina, laskea ja analysoida MPMK:n muutoksia ja niiden vaikutuksia valuma-alueen maaperän eroosioon ja sedimenttikuorman säätelyyn sekä tutkia yhteyttä valuma-alueen ylä- ja alajuoksun välillä sedimenttikuorman kontrolloinnissa Huatanay-joen valuma-alueella Cuscossa, Perun trooppisilla Andeilla.

Tutkimuksessa tuotettiin MPMK-kartat vuosille 1988, 1997 ja 2007. Vertailtaessa karttoja tilastollisesti saatiin yleinen kappa-indeksi 0.41 ajanjaksolle 1988-1997 ja 0.40 ajanjaksolle 1997-2007, mikä tarkoittaa tilastollisesti merkittäviä muutoksia MPMK-luokkien välillä tutkittuina ajanjaksoina. MPMK:n muutosten arviointi, jossa arvioidaan pinta-alan lisääntymistä ja vähenemistä MPMK-luokkien välillä, kertoi Huatanay-joen valuma-alueen olevan hyvin dynaamisessa tilassa, sillä useimmissa MPMK-luokissa muutos oli yli 50 % tutkittuina ajanjakoina. Useimmat MPMK:n muutokset johtuivat ihmisvaikutuksesta.

Arvioitu vuotuinen keskimääräinen maaperän häviö Huatanay-joen valuma-alueella oli 319.5, 299.4 ja 306.0 tonnia/ha/vuosi vuosina 1988, 1997 ja 2007, mikä tarkoittaa maaperän häviämisen lievästi vähentyneen MPMK:n muutoksista johtuen (P=0.009). Maaperän häviö oli kuitenkin kohtalaisen suurta, suurta tai erittäin suurta yli puolella valuma-alueen pinta-alasta, mikä tarkoittaa eroosio-ongelman olevan erityisen merkityksellinen kyseisellä valuma-alueella. Arvioitu sedimenttikuorma valuma-alueella oli 1260.37, 1201.48 ja 1227.61 tonnia/ km^2/vuosi vuosina 1988, 1997 ja 2007. Valuma-alueen ala-juoksulla, jossa sedimenttikuormat olivat suurimpia, sedimentaatio on erittäin aktiivista. Tästä on muodostunut ongelma, jota pahentaa kaupungin kasvu tulvatasangolle, joka on tärkeä alue sedimenttien kertymiselle. Tutkimuksessa todettiin myös selvä määrällinen suhde sedimenttien tuoton ja kertymisen välille. Maaperän eroosiota tapahtui pääasiassa valuma-alueen keski- ja yläjuoksulla, kun taas sedimenttien kertymistä pääasiassa valuma-alueen alajuoksulla.

Contents

1 Introduction

Human land use, particularly over the past 50 years, has changed ecosystems more rapidly and extensively than in any comparable period of time in human history. This has occurred as a consequence of rapidly growing demand on natural resources (Watson & Zakri 2003). It has resulted in degradation of the natural ecosystem functioning. Thus, to understand land cover and land use change process and its implication for environmental and ecosystem functioning, it is important to recognize the services provided by the natural ecosystems, and to come up with a sustainable land use plan.

However, the study of the human impact on the environment and its functioning is a great challenge. The development of suitable and reliable indicators which can provide all essential information about the viability of a system and its rate of change and about how that contributes to sustainable development of the overall system is a key issue (Bossel 1999). Nowadays, this kind of assessment is greatly helped by the data provided by the modern earth observing systems. Remote sensing techniques together with Geographical Information Systems (GIS) increase the capability to analyze the dynamic environment and human impact on the environment by using quantitative (hard number), qualitative (subjective valuation) and spatial form.

This study is carried out in the Huatanay watershed of the tropical Andes of Peru, an urbanized watershed under an intense land use, which is largely modifying the natural land cover and having several impacts on the local ecosystem functioning. The urban and suburban growth and the agricultural and livestock practices in steep slopes have a strong impact to soil erosion increasing sediment load to water streams. Sediment is a major pollutant, a transport of pollutant, and sedimentation rate and amount determine the performance and life of reservoirs, canals, drainage channels etc. (Lane *et al*. 1997). Sediment accumulation also contributes to risk of flooding. In the Huatanay river basin, several projects have been executed, where millions of dollars have been invested for river canalization, water cleaning and flood control, but due to the rapid infrastructure deterioration as a consequence of sediment accumulation, urban sewage and industrial wastewater discharge into the river, violent storm runoffs, flooding and solid waste accumulation, and the problem is not solved.

As watershed management nowadays trends towards market-based approaches through recognition and valuation of environmental services, it is operationalized by a scheme of payment for ecosystem services (PES) (Mayrand & Paquin 2004). Within a watershed a deep understanding of the interplay between biological and hydrological processes and the factors that regulate and shape them is needed (Zalewski & Wagner-Lotkowska 2004). It is assumed that regulating hydrological, biotic and landscape interactions and processes, through using e.g. vegetation and its natural services for environmental quality improvement (phytotechnology), contribute to improve ecosystem resistance to stress, to the maintenance of a homeostatic equilibrium within an ecosystem, and to the possibility of augmenting ecosystem resilience to anthropogenic changes. It can also provide socio-economic benefits on its own (Zalewski & Wagner-Lotkowska 2004).

2 Objective

A general objective of this study is to assess the spatially and temporally dynamic pattern of the land cover and land use, and its impact on the watershed regulation services to support environmental planning.

Specific Objectives

- Generate multi-temporal land cover and land use information using Landsat Thematic Mapper (TM) satellite data for the Huatanay watershed.

- Analyze the land cover and land use change pattern and identify the main driving factors.

- Model and quantify spatially the critical areas impacted by LCLU change on soil loss and sediment yield rate through the watershed.

- Identify the relationship between the upper and lower parts of the watershed on sediment regulation.

3 Theoretical Framework

3.1 Watershed Ecosystem Services and Valuation

The term “ecosystem services” or “environmental services” refers to the conditions and processes through which natural ecosystems sustain and fulfill the needs of human life (Daily 1997, Kremen & Ostfeld 2005). These services are a result from ecosystem functions, the physical, chemical, and biological processes that the ecosystem does for self-maintenance (King & Mazzotta 2000). Ecosystem services are generally divided into four categories: Provisioning services – e.g. food, fresh water, fuel wood, genetic resources; Regulating services – e.g. climate regulation, pest and disease regulation, hazard mitigation, control of soil erosion and sedimentation, and water quality regulation; Cultural and amenity services – e.g spiritual, recreational, aesthetic, inspiration, educational; Supporting services – which represents the ecological process that underlie the functioning of the ecosystem (Hein *et al.* 2006) or those needed for the provision of the other services – e.g. wildlife habitat, soil formation, nutrient cycling, primary production (Watson & Zakri 2003).

Ecosystem services are supplied to the economic system at a range of spatial and temporal scales, varying from the short-term, site level (e.g. amenity services) to the long-term, global level (e.g. carbon sequestration) (Turner *et al*. 2000, Limburg *et al*., 2002, Hein *et al*. 2006). Ecosystems can be defined at a wide range of spatial scales; they vary from the level of individual plant, via ecosystems and landscape, to global systems (Hein *et al*. 2006). Similarly, the socio-economic system present an institutional scale or hierarchy from the level of individual and households to communal, municipal, provincial, national, and international higher levels, at which decision on the utilization of capital, labor and natural resources are taken (North 1990, Hein *et al.* 2006). Scales and stakeholders are often correlated, as the scales at which ecosystem services are supplied determine which stakeholders may benefit from it (Vermeulen & Koziell 2002, Hein *et al.* 2006).

Watershed, also called catchment or river drainage basin, is a basic environmental unit where water drains downhill into a common stream (Gordon *et al*. 2004). The several components that encompass the landscape within a watershed (forests, grasslands, cultivated areas, riparian areas, wetlands, etc.) form groups of ecosystems. These ecosystems provide ‘watershed services’ (Smith *et al*. 2006). Watershed services are controlled by the ways of land and water use in watersheds (Smith *et al*. 2006). Increasing degradation of watersheds has led to increased recognition of the services they provide. This is reflected in numerous initiatives, in which market-based instruments and other supporting institutional arrangements are used as a way to create incentives and to recover the costs of watershed protection (Tognetti *et al*. 2005).

Several techniques for valuing ecosystem services have being developed. However, there is no satisfactory method to measure the full dimension of ecosystem services (Acreman 2004). A general framework for ecosystem services valuation is presented by Hein *et al.* (2006), based upon the works by Pearce & Turner (1990), Constanza & Folke (1997), De Groot *et al.* (2002) and Watson & Zakri (2003). It is profiled in Fig. 1.

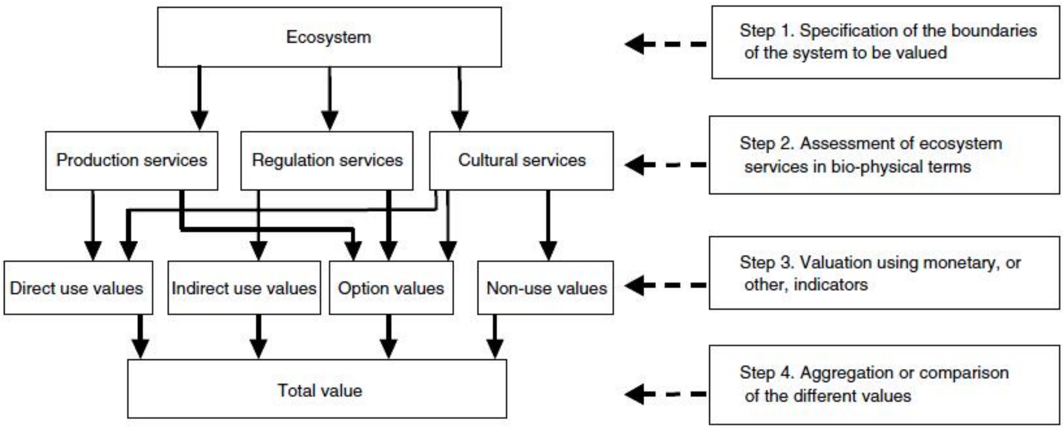

Figure1. The ecosystem valuation framework (Hein *et al*. 2006).

Valuation requires that the ecosystem object to be valuated is clearly identified and limited (Hein *et al.* 2006) and a clear cause-and-effect relationships between land use and the provision of watershed services can be established (Smith *et al.* 2006). Then, the watershed services have to be assessed in bio-physical terms (Hein *et al.* 2006), and therefore it is important to define and quantify indicators to track the delivery of services and to assess which users benefit from it (Smith *et al.* 2006). For most regulation services, quantification requires spatially explicit analysis of the bio-physical impact of the services on the environment at or surrounding the ecosystem patch being studied. However, a regulation service such as carbon sequestration doesn't usually require spatially explicit assessment, because the value of the carbon storage doesn't depend on where it is sequestered. Cultural services depend on human interpretation of the ecosystem, or of specific characteristics of the ecosystem (Hein *et al.* 2006). They are also called “information services”. Supporting services are not included in ecosystem service valuation, because they may lead to double counting. Their value is reflected in the others types of services. In addition, there are several ecological processes that underlie the functioning of ecosystems, and it is unclear on which basis supporting services should be included in or excluded from a valuation study (Hein *et al.* 2006).

Following the ecosystem valuation process, each ecosystem service must have an attributed value. Even though, the term value has a range of meanings in different disciplines, generally it means the contribution of an action or object to user-specified goals, objectives or conditions (Constanza 2000, Farber *et al*. 2002). In economic sense, first Aristotle distinguished between value in use and value in exchange explained by the diamond-water paradox, where water has infinite or indefinite value being necessary for life but low exchange value, while the unessential diamonds have a high exchange value. Later on Galiani noted that value depends on utility and scarcity (Schumpeter 1978, Farber *et al*. 2002). Smith formulated a cost of production value, where wages, profit and rent are the three original sources of exchange values (Farber *et al*. 2002). The exchange values of ecosystem services are the trading ratios for those services. When services are directly tradable in normal markets, the price is the exchange value. The exchange-based welfare value of a natural good or service is its market price net of the cost of bringing that services to market. i.e. the exchange-based value of timber to society is its “stumpage rate”, which is the market price of timber net of harvest and time allocation management cost (Farber *et al.* 2002). The underlying concepts for social values that economists have developed are what a society would be willing and able to pay for a service (WTP), or what it would be willing to accept to forego that services (WTA) (Farber *et al*. 2002). The economic valuation methodology essentially constructs

WTP for a service, or constructs the adequate compensation for a service loss, representing WTA. Farber *et al*. (2002) describe six major ecosystem services economic valuation techniques when market valuations do not adequately capture social value: 1. Avoided Cost (AC), services allow society to avoid cost that would have been incurred in the absence of those services; 2. Replacement Cost (RC), services could be replaced with man-made systems, which may be costly; 3. Factor Income (FI), services provided for the enhancement of incomes; 4. Travel cost (TC), service demand may require travel, whose costs can reflect the implied value of the services. 5. Hedonic Pricing (HP), services demand may be reflected in the price people will pay for associated goods, 6. Contingent Valuation (CV), services demand may be elicited by posing hypothetical scenarios that involve some valuation of alternatives. Some ecosystem services may require that several techniques are used jointly.

A widely used framework for valuation of ecosystem services is based on the concept of Total Economic Value (TEV). Total Economic Value is typically disaggregated into two categories: (1) Use values and (2) Non-use values (Smith *et al.* 2006). Use value is composed of three elements: (1a) Direct-use value, resources or goods that can be extracted, consumed or enjoyed directly (i.e. drinking water, timber, hydropower, and recreation parks), (1b) Indirect-use value, which mainly derives from the services that the environment provides (i.e. regulation of river water flows quality and quantity, flood control, erosion and sediment transport control, etc.), and (1c) Option value, which is the value attached to maintaining the possibility of obtaining benefits from ecosystem goods and services at a later date (Smith *et al.* 2006). Non-use values, on the other hand, derive from the benefits the environment may provide that do not involve using it in any way, whether directly or indirectly, i.e. people place value on the existence of blue whales or pandas, even if they have never seen one (Smith *et al*. 2006).

The final step of valuing ecosystem services is the aggregation or comparison of the values of valuation trying to obtain the total value of ecosystem services. If all values have been expressed as a monetary value and the values are expressed through comparable indicators, the use value and non-use value can be summed. If non-monetary indicators are used for the non-use values, the values can be presented side-by-side (Hein *et al.* 2006), or alternatively, they can be compared using Multi Criteria Assessment (MCA), and stakeholders can be asked to assign relative weights to different sets of indicators (non-monetary as well as monetary), enabling comparison of indicators (Nijkamp & Spronk 1979, Constanza & Folke 1997, Hein *et al*. 2006).

3.2 Watershed Management and Watershed Services

Watershed management concept and strategies have been gradually developed and adopted. They have emerged in European countries for flood and debris control of mountain streams and their drainage basins, and then adopted in North America emphasizing gradually on managing watershed for water benefit (water yield, water quality and flood prevention), and later extended to developing countries focusing on land management, erosion and sedimentation and flood control. Nowadays, watershed management has focused on the whole watershed system, integrating the human and social development involved and environmental managing, emerging the terms of Integrated Watershed (or Catchment) Management (IWM) (Sheng 1999), integrated river basin management (IRBM), and integrated water resources management (IWRM), which are equivalent terms for a specific kind of Environmental Managenment– one in which the unit of analysis is a hydrologic catchment (Abell *et al*. 2002).

As a watershed system is very complex and involves different stakeholders, watershed programs or projects do not benefit all equally. In most developing countries the watershed upstream inhabitants are mostly small farmers, whereas downstream people are middle class town or city dwellers. Government investments usually aim protecting downstream interests such as reservoirs, irrigation installation, waters supply schemes, electric generation stations and road and bridges from sedimentation or flood damages. Upstream inhabitants may not share these benefits; they simply have no electricity, irrigated water or treated water in their watersheds. On the other hand, some programs have stressed the production function of the watershed, especially for increasing crop and animal production on individual farms in a watershed. Such approaches merely include soil conservation and crop or animal development programs without integrating downstream water protection (Jeanes *et al*. 2006).

Implementation of watershed management is generally costly and small farmers have no resources to do it. In addition, the benefits may take several years or even generation to realize, or they occur at elsewhere in the downstream area. Farmers are providing land, labor or time for conservation work, and compensation from the beneficiary stakeholders or government is needed. Incentives can be an equitable distribution of income, considering that the town or city people receive much more from the government in terms of infrastructure. These urban inhabitants need to share a part of the cost of watershed work in upstream (Sheng 1999).

The nature of watershed management work relates to many disciplines and multiple sectors, which raises many controversial issues for planning and implementation. Common problems encountered with integrated watershed management are the conflicts of interest between downstream and upstream people when both are involved in the planning process (Sheng 1999). The downstream community, being located at the receiving end, prefers more protection and conservation work while the upstream inhabitant demand more rural development. How to strike a balance between conservation and development with limited funds is a serious challenge to watershed planners (Achouri 2005). In most watershed projects, funds are not even sufficient for comprehensive protection or rehabilitation of a watershed. If a part of the funds is to be used for rural development, the major task of watershed management will be either delayed or scarified, defeating its main purpose.

Watershed management nowadays trends towards market-based approaches, through recognition and valuation of environmental services. It is realized by a scheme of payment for ecosystem services (PES) (Mayrand & Paquin 2004). Economic valuation can be useful, by providing a way to justify and set priorities for programs, policies or actions that protect or restore ecosystems and their services (King & Mazzota 2000).

Payments for ecosystem services (PES) is the name for a variety of arrangements through which the beneficiaries of ecosystem services compensate, reward or pay back the providers of those services (Wunder 2005). Different types of payments schemes are possible. A private scheme involves direct payment to service providers, the purchase of land or the sharing of costs among involved private parties. A cap and trade scheme establishes a cap for water abstraction or pollution and enables trading of permits among water users. A certification or eco-labeling scheme, where the costs of services are included in the price paid for a traded product. And, public payment schemes, the most commonly used schemes, which involve public agencies and include user fees, land purchase and granting of rights to use land resources, as well as fiscal mechanisms based on taxes and subsidies (Smith *et al*. 2006). Several case studies are presented in Gudman (2003), Mayrand & Paquin (2004), Scherr *et al*. (2006) and Lipper & Nelson (2007).

3.3 Land Cover and Land Use Data from Remotely Sensed Data

Remote sensed data provides the capability to monitor a wide range of landscape biophysical properties important to management and policy, where information on these variables is needed in the past, present and future (McVicar *et al*. 2003). However, remote sensed data are not capable to register the internal structural composition of the landscape, such as species composition of communities, soil chemical characteristics, soil management practices, etc. Remote sensed techniques need to be combined and complemented with in-situ measurements and modeling systems of terrestrial processes and climate (McVicar *et al*. 2003).

Satellite-based remotely sensed data is commonly recorded in digital form as a grid of cells or pixels. The data file value assigned to each pixel is the record of reflected radiation or emitted heat from the earth's surface at that location (Pouncey *et al*. 1999). Pixel value in commercially available imagery represent the radiance of the surface in the form of digital numbers (DN), which are calibrated to fit a certain range of values, e.g. from 0 to 255 in an image of 8 bits (Varlyguin *et al*. 2004). In remotely sensed data four distinct types of resolution must be considered: spectral (the specific wavelength intervals that a sensor can record), spatial (the area on the ground represented by each pixel), radiometric (the number of digital levels into which the radiance of the surface recorded by the sensor is divided and expressed; this is commonly expressed as the number of bits) and temporal (how often a sensor obtains imagery of a particular area) (Pouncey *et al*. 1999). Conversion of DN back into absolute radiance is a necessary procedure for comparative analysis of several images acquired at different times which allows more accurate comparison of images across rows, paths and dates (Varlyguin *et al*. 2004).

There exist several imagery satellites with very different imaging characteristics, e.g. Landsat series, Spot, Aster, Ikonos, Quick Bird, Geoeye, etc. Landsat series of satellites is a primary environmental data source. It has provided a continuous coverage since 1972 to nowadays through its Multi-spectral scanner (MSS), Thematic mapper (TM) and enhanced TM sensor (ETM) (Guindon & Zhang 2002). A detailed Landsat satellite series characteristic description is given by Short (1999).

Remotely sensed data is not free of errors. Error or noise is introduced into the remotely sensed data by: the environment (e.g., atmospheric scattering), or random or systematic malfunction of the remote sensing system (e.g., an uncalibrated detector creates striping). Therefore, the quality and statistical characteristics of digital remote sensor data should first be assessed. This assessment can be assisted by using exploratory data analysis techniques (Jensen 2004).

The satellite image processing and analysis refers to the act of examining images for the purpose of detecting, identifying, classifying, measuring and evaluating the significance of physical and cultural objects, their patterns and spatial relationship (Pouncey *et al*. 1999). The image processing can broadly be categorized into: pre-processing, image classification or segmentation, post processing and evaluation (Jensen 2004). Detailed image processing procedures are explained in, e.g., Pouncey *et al.* (1999) and Jensen (2004).

Common pre-processing techniques include: Radiometric and geometric correction, Radiometric enhancement, Spatial enhancement, Spectral enhancement, and Fourier analysis. Radiometric correction addresses variations in the pixel intensities (DNs) that are not caused by the object or scene being scanned. Several algorithms have been developed to radiometric correction (Jensen 2004). Since spatially varying haze is a common feature of archival Landsat TM scenes, which can affect the image classification quality, an important pre-processing step to information extraction is haze reduction (Guindon & Zhang 2002). Haze Reduction method (Algorithm available in Erdas Image for Landsat TM) for multi-spectral images, is based on the Tasseled Cap transformation which yields a component that correlates with haze. This component is removed and the image is transformed back into RGB (red, green and blue) space (Pouncey *et al*. 1999).

An additional consideration to take into account using remotely sensed data in mountainous region is that digital imagery from mountains often contains a radiometric distortion known as topographic effect. Topographic effect results from the differences in illumination (the amount of reflected energy) due to the angle of the sun and the angle of the terrain. This causes a variation in the image brightness values (Hodgson & Shelley 1994, Pouncey *et al*. 1999). One way to reduce topographic effect in digital imagery is by applying transformations based on the Lambertian or Non-Lambertian reflectance models, using information on solar elevation and azimuth at the time of image acquisition, terrain characteristic (DEM) and original imagery (after atmospheric corrections). These models normalize the imagery, which make them appear as if they were representing a flat surface (Pouncey *et al*. 1999). Törmä & Härmä (2003), Riaño *et al*. (2003), Law & Nichol (2004) among several other researchers have tested different models of topographic normalization methods. However, no common agreement in the best approach has been found. Thus, as Varlyguin *et al*. (2004) state, most of these techniques are still under development for a reliable application.

Also, in mountain areas, errors due to the sensor viewing geometry and terrain variation may be introduced. These causes distort the obtained satellite images and significant terrain displacements can occur, but in a smaller scale than in aerial photographs (Varlyguin *et al.* 2004). In a nadir-viewing sensor (perpendicularly downward-facing viewing geometry) only the scene center pixels are not distorted, but other pixels, especially those in the view periphery, are distorted due to off-nadir view. Here a rigorous geometric correction utilizing DEM and sensor position information to correct these distortions (orthocorrection) is needed (Short 1999). Polynomial equations are used to convert source file coordinates to rectified map coordinates. Since the pixels of the new grid may not align with the pixels of the original grid, the pixels are resampled interpolating data values for the pixels on the new grid using the values of the source pixels (Jensen 2004). The selection of the resampling method depends on the usage of the resulting image and the degree of image distortion. For image classification usually the nearest neighbor method is recommended, because it transfers original data values without averaging them as most other methods do, and therefore the extremes and subtleties of the data values are not lost. This is an important consideration when discriminating between vegetation types, locating an edge associated with a lineament or determining different levels of turbidity or temperatures in a lake (Jensen 2004).

There are several methods for the image classification, and the choosing of the most appropriate method will always depend on the characteristics of the image and the type of analysis being performed (Eastman 2006a). Satellite image classification into land cover categories is based on the fact that land cover types have unique spectral response patterns; hence, spectral pattern recognition can be more important (Eastman 2006b). The classification process breaks down into two parts: training and classifying (using a decision rule) (Pouncey *et al*. 1999). Training is the process of defining the criteria by which these patterns are recognized (Hord 1982, Pouncey *et al*. 1999). Training can be performed with either an unsupervised or supervised method (Hastie *et al.* 2003). However, both methods have some drawbacks; unsupervised training doesn't guarantee that the classification makes sense for the interpreter, and supervised training results in many cases a subjective classification, because the interpreter has previously established the categories without taking into account the full spectral characteristics in the image (Chuvieco 2002). Using a combination of supervised and unsupervised classification may yield optimal results, especially with large data sets (e.g. multiple Landsat scenes). For example, unsupervised classification may be useful for generating a basic set of classes, and then supervised classification can be used for further definition of the classes (Chuvieco 2002).

An important step for image classifying process is the evaluation of signatures; there are several tests to perform whether the signature data is a true representation of the pixels to be classified for each class. The Divergence and its variant the Transformed divergence (Equations 1 and 2) are easily interpretable methods to evaluate the signature separability based on a statistical measure of distance (Euclidean) between two signatures. If the spectral distance between two samples is not significant for any pair of bands, then they may not be distinct enough to produce a successful classification (Pouncey *et al*. 1999).

Divergence (D_{ij}):

$$D_{ij} = \frac{1}{2}tr((C_i - C_j)(C_i^{-1} - C_j^{-1})) + \frac{1}{2}tr((C_i^{-1} - C_j^{-1})(\mu_i - \mu_j)(\mu_i - \mu_j)^T) \quad (1)$$

where: i and j = the two signatures (classes) being compared, C_i = the covariance matrix of signature i, C_j = the covariance matrix of signature j, μ_i = the mean vector of signature i, μ_j = the mean vector of signature j, tr ( ) = the trace function (matrix algebra), $^{-1}$ = matrix inverse, and ^{T} = transpose (matrix algebra) (Swain & Davis 1978, Pouncey et al. 1999).

Transformed Divergence (TD):

$$TD_{ij} = 2000\left(1 - \exp\left(\frac{-D_{ij}}{8}\right)\right) \quad (2)$$

where the divergence (D_{ij}) of signatures i and j (classes) is being compared (calculated with the equation 1). 2,000 is an introduced constant to scale the divergence result values to the known range, some authors recommend to use 100 to interpret the divergence values as percent (Swain & Davis 1978, Pouncey *et al*. 1999).

According to Jensen (2004), the transformed divergence “gives an exponentially decreasing weight to increasing distances between the classes.” The scale of the divergence values can range from 0 to 2,000. Interpreting the results after applying transformed divergence requires analyzing those numerical divergence values. As a general rule, if the result is greater than 1,900, then the classes can be separated. Between 1,700 and 1,900, the separation is fairly good. Below 1,700, the separation is poor (Jensen 2004).

Then classification decision rules are selected, non-parametric or parametric. A non-parametric decision rule is not based on statistical descriptors. Therefore, it is independent of the properties of the data. If a pixel value is located within the upper and lower limits of a defined nonparametric signature, then this decision rule assigns the pixel to the signature’s class (Kloer 1994, Pouncey *et al*. 1999). A parametric decision rule is based on the statistical descriptors (mean and covariance matrix) of the pixels that are in the training sample for a certain class. The Maximum Likelihood Decision Rule is the most widely used and accurate of the parametric classifiers. It is based on the probability that a pixel belongs to a particular class. The basic equation (equation 3) assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. Or if there is a priori knowledge that the probabilities are not equal for all classes, weight factors can be specified for particular classes. This variation of the maximum likelihood decision rule is known as the Bayesian decision rule (Hord 1982, Pouncey *et al*. 1999).

$$D = \ln(a_c) - [0.5 \ln(|Cov_c|)] - [0.5 (X-M_c)^T(Cov_c^{-1})(X-M_c)] \quad (3)$$

where D = weighted distance (likelihood), c = a particular class, X = the measurement vector of the candidate pixel, M_c = the mean vector of the sample of class c, a_c = percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from a priori knowledge), Cov_c = the covariance matrix of the pixels in the sample of class c, $|Cov_c|$ = determinant of Cov_c (matrix algebra), Cov_c^{-1} = inverse of Cov_c (matrix algebra), ln( ) = natural logarithm function, and ^{T} = transpose (matrix algebra) (Pouncey *et al*. 1999).

However, the Maximum likelihood relies heavily on a normal distribution of the data in each input band and tends to overclassify signatures with relatively large values in the covariance matrix. If there is a large dispersion of the pixels in a cluster or training sample, then the covariance matrix of that signature contains large values (Jensen 2004).

Classified images require post-processing to evaluate classification accuracy, reduce isolated pixels, and improve map representation, among other purposes. A very common post processing operation is to generalize the image through a low pass filter over the classified result and fuzzy convolution using the distance error image file generated during the parametric classification (Pouncey *et al*. 1999). Land cover maps derived from remotely sensed data inevitably contain errors of various types and degrees. It is therefore very important that the nature of these errors is determined, in order for both users and producers of the maps to be able to evaluate their appropriateness for specific uses (Congalton & Green 1998, Maingi *et al.* 2002).

The error matrix is commonly used for reporting the accuracy of maps derived from remotely sensed data (Congalton & Green 1993, Maingi *et al*. 2002). More recent research into classification accuracy assessment has focused on factors influencing the accuracy of spatial data, such as sampling scheme and sample size, classification scheme, and spatial autocorrelation (Congalton 1991, Congalton and Green 1993, Maingi *et al*. 2002). Other important considerations in classification accuracy assessment include ground verification techniques and evaluation of all sources of error in the spatial data set.

An error matrix compares the classification to ground truth or other data (existing maps), reporting calculated statistics of the percentages of accuracy based upon the results of the error matrix (Pouncey *et al*. 1999). An error matrix technique is appropriate for remotely sensed data which is discrete data rather than continuous data. The data are also binomially or multinomially distributed, and therefore, common normal distribution based statistical techniques do not apply (Jensen 2004).

Kappa coefficient is also applied to image classification evaluation. It estimates accuracy considering agreement that may be expected to occur by chance (Maingi *et al*. 2002). Verbyla (1995), in Maingi *et al*. (2002), gives a formula (5) for computing K coefficient:

$$K = \frac{\text{Overall classification accuracy} - \text{Expected classification accuracy}}{1 - \text{Expected classification accuracy}} \qquad (4)$$

where the Kappa coefficient expresses the proportionate reduction in error generated by a classification process compared with the error of a completely random classification. Overall accuracy uses only the main diagonal elements of the error matrix, and as such it is a relatively simple and intuitive measure of agreement (Maingi *et al*. 2002). However, because it does not take into account the proportion of agreement between data sets that is due to chance alone, it tends to overestimate classification accuracy (Congalton & Mead 1983, Congalton *et al*. 1983, Rosenfield & Fitzpatrick-Lins 1986, Ma & Redmond, 1995, Maingi *et al.* 2002).

3.4 Land Cover and Land Use Change (LCLU) Theories, Models and Detection Methods.

The land supports all the human activities, providing goods (resources) and services (regulations) (Turner II *et al*. 2007) and receiving disposal. Land use is being dynamically shaped under the influence and interaction of two broad sets of forces – human needs and environmental features and processes (Briassoulis 2006). Change in the use of land occurring at various spatial and temporal levels (Argawal *et al*. 2002). These changes have at certain times beneficial, and at other times detrimental impacts (Briassoulis 2006), the latter being the main cause affecting the structure and functioning of ecosystems (and ultimately, the earth system) as well as the human well-being (Turner II *et al*. 2007).

Definition and description of land cover, land use and land use change vary with the purpose of the application and the context of their use. The land cover is the biophysical state of the earth's surface and immediate subsurface (Turner II *et al*. 1995, Briassoulis 2006), while the land use denotes the human employment of the land (Turner II & Meyer 1994, Briassoulis 2006) and land-cover type (Skole 1994, Briassoulis 2006).

Land cover and land use change means changes in structure and function (qualitative) and change in the areal extent (quantitative) of a given type of land use or cover (Seto *et al*. 2002). Furthermore, in case of land cover change, two types of changes can be distinguished (Turner II *et al*. 1995, Skole 1994, Briassoulis 2006): Conversion, which means a change from one cover type to another, and modification, which means alteration of structure or function without a complete change from one type to another; it could involve change in productivity, biomass, or phenology (Skole 1994, Briassoulis 2006). Land cover change occurs as a result of natural process such as climatic variation, volcanic eruptions, change in river channels or the sea levels, etc. However, most of the land cover changes of the present and the recent past are due to human actions – i.e. to using of the land for production or settlement (Turner II *et al*. 1995, Briassoulis 2006). Similarly, land use change involves conversion from one type of use to another. Modification of a particular land use may involve change in the intensity of this use as well as alteration of its characteristics qualities/attributes. In the case of agricultural land use, Jones & Clark (1997) provide a qualitative typology of land use change: intensification, extensification, marginalization and abandonment (Jones & Clark 1997, Briassoulis 2006).

The reason why the linkage between land use and land cover change is emphasized is that the environmental impacts of land use change and their contribution to global change are mediated to a considerable extent by land cover change (Briassoulis 2006). Thus, their analysis needs the examination of the ways in which land use relates to land cover change at various levels of spatial and temporal detail. Local level land use change may not produce significant local land cover change (and consequently, no significant environmental impact). However, they may accumulate across space and/or over time and produce significant land cover change at higher (e.g. regional, national or global) levels (Briassoulis 2006). This is the case for example of agricultural land conversion to urban uses that results from the decisions of individual land owners to convert their farmland to non-farm uses. Though not physically connected through a globally operating system, these changes can reach a global scale and status when their occurrence in many places adds up (Briassoulis 2006). Land degradation, desertification, biodiversity loss, deforestation and wetland drainage have all amounted to a globally significant alteration of the land cover class involved (Meyer & Turner II 1996, Briassoulis 2006).

The analysis of land use change revolves around two central and interrelated questions: "what drives/causes land use" and "what are the environmental and socio-economic impacts of land use chage" (Briassoulis 2006). The precise meaning of the "drivers" or "determinants" of land use is not always clear. However, there are two main categories widely accepted: biophysical and socio-economic drivers (Briassoulis 2006). The biophysical drivers include characteristic and process of the natural environment such as: climate variation, landform, and geomorphic process, plant succession, soil types and process, drainage pattern etc. The socio-economic drivers comprise demographic, social, economic, technological, market, political and institutional factors and their processes (Briassoulis 2006).

The impacts of land use change are broadly categorized into environmental and socio-economic, but it should be noted that environmental and socio-economic impacts are closely interrelated; the former causing the latter which then feedback to the former again, potentially causing succession rounds of land use change (Briassoulis 2006).

Several theories of land use change intend to describe the structure of the change in the use of land from one type to another and explain why these changes occur, what causes these changes, what are the mechanisms of changes. The “what” and the “why” of land use change are closely related although existing theories rarely address both (Briassoulis 2006).

The majority of theories of land use change lay in the more general theoretical framework of discipline studying economic, environmental and spatial change (or transformation). Briassoulis (2006) classified theories of land use change into three main categories: the urban and regional economics theories, the sociological (and political economy) theories, and the nature-society (or human-nature) theories, which address mainly the human role in causing global environmental change.

Land use change is the result of a complex web of interactions between bio-physical and socio-economic forces over space and time (Briassoulis 2006). Dealing with this complexity for practical purposes (such as policy making and land management for sustainable land use) is impossible without some simplification of the complex relationships to manageable and understandable dimensions. Hence, there is a need for a model (land use change model) which expresses operationally the relationships between the main factors of interest (Turner II *et al*. 1995, Briassoulis 2006).

According to Briassoulis (2006) land use change models can be used for several purposes: (1) to provide decision support in various decision and policy making contexts, (2) to describe the spatial and temporal relationships between the drivers and the resulting patterns of land uses and their changes, (3) as explanatory vehicles of observed relationships, (4) to predict (or forecast) future configurations of land use patterns under various scenarios of bio-physical (e.g. climatic) and socio-economic change, (5) as a an instrumental role in impact assessment of past or future activities in the environmental and/or the socio-economic spheres, (6) to prescribe "optimum" patterns of land use for sustainable use of land resources and development, and (7) to evaluate a set of land use alternatives which have to be evaluated on the basis of specific criteria. It should be noted that in several operational models (step 3) explanation is reduced to statistical or mathematical explanation which is not necessarily equivalent to theoretical explanation which attempts to get into the causality of the relationships analyzed and modeled.

Some theories and models have been conceived simultaneously in which case the terms "theory" and "model" are used interchangeably to denote a set of theoretical and operational statements about reality (such as von Thunen’s and Alonso’s theories and models). However, there is a lack of a clear theory in several models (Briassoulis 2006).

According to dominant model design feature, solution technique, and spatial and temporal levels of analysis the following broad categories of models are distinguished: (1) empirical-statistical models (multivariate techniques and regression models, which are mainly exploratory tools), (2) stochastic models (represented by a Markov chain, mainly transition probability models) (Lambin 2004), (3) optimization models (the linear programming models family, which are prescriptive models although they are used also as evaluation tools) (Briassoulis 2006), (4) dynamic process-based simulation models (which emphasize the interactions among all components forming a systems and attempt to imitate the run of these process and follow their evolution, also condensing and aggregating complex ecosystems into a small number of differential equations in a stylized manner) (Lambin 2004) and (5) connectionist models (cellular automata and neural networks, which attempt to respond to the need to account for the important role of spatial detail in many real world systems) (Briassoulis 2006).

The change detection is the process of identifying differences in the state of an object or phenomenon by observing and quantifying it at different times (Singh 1989, Lu *et al*. 2004a). Land cover and land use (LCLU) change detection is important for monitoring change of earth’s surface features to understand the relationships and interactions between human and environment to a better management and use of natural resources (Lu *et al*. 2004a). In general, change detection involves the application of multi-temporal datasets (mostly remotely sensed data) to quantitatively analyze the temporal effects of the phenomenon (Lu *et al*. 2004a).

Research of change detection techniques is an active topic, and several techniques are available and constantly developed. Some of the most common methods used for LCLU change detection are image differencing, principal component analysis, and post-classification comparison (Lu *et al*. 2004a). As changes of the multi-temporal images are usually complex and non-linear, non-linear change detection theories and methods have great significance in solving change detection. Relative techniques in pattern recognition which should be more tightly integrated within change detection methods are: Artificial neural networks (ANN) - A connectionist adaptive system that changes its structure based on external or internal information feedback that flows through the artifitial neurons network during a learning phase; Kernel theory - a weighting function used in non-parametric estimation techniques; Data mining and knowledge discovery methods (Jianya *et al*. 2008).

As a general overview, change detection approaches can be characterized in two groups: bi-temporal change detection (direct comparison, post-analysis comparison and uniform modeling) and temporal trajectory analysis (time series analysis). The former measures changes based on a simple 'two-epoch' timescale comparison. The latter analyses the changes based on a 'continuous' timescale, focusing both changes between dates and the progress of the change over the period (Jianya *et al*. 2008). Almost all classifications for change detection algorithms are based on bi-temporal change detection and little attention is paid to temporal trajectory analysis (Jianya *et al*. 2008). Also other classifications for change detection methods have been proposed. Deer (1995) classifies them into three categories: pixel-based, feature-based and object-based change detection methods. Jianya *et al*. (2008) based on Lu *et al*. (2004a) classifies the methods into seven groups: direct comparison, classification comparison, object-oriented methods, model-based methods, time-series analyses, visual analyses, and hybrid methods.

A good change detection research should provide the following information: area change and change rate, spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of change detection results. The accuracies of change detection results depend on the performance of the image processing and classification approach, availability of good-quality true data, the complexity of landscape and the environment of the study area, appropriate change detection methods or algorithms used, and the analyst's skills and experience as well as knowledge and familiarity of the study area, time and cost restrictions (Lu *et al*. 2004a).

A straightforward method to detect changes in terms of thematic classes is by cross-tabulation and cross-classification using two geo-referenced images of the same area, taken at different dates and classified to the same set of *N* classes. A simple raster overlay will exactly indicate for each pixel to which class it belongs at both moments in time (Lu *et al*. 2004a). This gives *N*N* possible values, although only a subset of these will occur in a significant number of pixels. The procedure is summarized by a cross-tabulation matrix (also known as the confusion matrix) that shows the joint distribution of image cells between classes. A Kappa Index of Agreement (KIA) is calculated as a cross-tabulation output as:

$$\text{KIA} = \{\text{observed accuracy} - \text{chance agreement}\} / \{1 - \text{chance agreement}\} \tag{5}$$

KIA values range from –1 to +1 after adjustment for chance agreement. If the two input images are in full agreement (images are identical and no change has occurred), K equals 1. If the two images are in full disagreement (the images are opposite, complete transformation in a consistent manner), K takes a value of –1. If the change between the two dates occurred by random (no correlation), then Kappa equals 0 (Lorup 1996). The per-category K can be calculated using the formula 6 (Rosenfield & Fitzpatrick-Lins 1986, Thiam 1998):

$$K_i = (P_{ii} – (P_i*P_{i'})/(P_i – P_i*P_{i'}) \quad (6)$$

where: P_{ii} = Proportion of entire image in which category i agrees for both dates, P_i = Proportion of entire image in class i in reference image, $P_{i'}$ = Proportion of entire image in class i in non-reference image. The per-category agreement index (K_i), indicates how much category i has changed between the two dates.

Although the most efficient and widely-used techniques in the accuracy assessment of change detection, like in remotely sensed image classification, are based on the error matrix of classification, some alternative methods also exist. Such methods include field survey with the assistance of historical GIS data, local people knowledge, simultaneous or within time proximity high-resolution images and visual interpretation. For long-time temporal trajectory change detection, it is more difficult to obtain ground reference data (Jianya *et al*. 2004). When the ground reference is unavailable, the consistency check rules are often employed to assess accuracy. Liu & Zhou (2004) proposed an accuracy analysis of time series of remote sensing change detection by rule-based rationality evaluation with post-classification comparison.

An important tool to analyze LCLU change is the Land Use Change Modeler (LCM) algorithm, developed by Clark Labs of University of Clark and the Andes Center for Biodiversity Conservation of Conservation International. The LCM is oriented to processing problems related to accelerated land conversion and the specific analytical need of biodiversity conservation. LCM is organized around a set of five major task areas expressed as: analyzing past land cover change, modeling the potential for land transitions, predicting the course of change into the future, assessing its implication to biodiversity, and evaluating planning intervention for maintaining ecological sustainability. A more thorough explanation of the methods is given in Eastman (2006a). For the purpose of LCLU change analysis, LCM is based on two remote sensing data derivates, earlier and later, computing gains and losses of categories, net change contribution, persistence and trend reporting them numerically and graphically (Eastman 2006b).

3.5 Soil Erosion and Sediment Yield Modeling at Watershed Scale

A variety of human land uses disturb the land surface of the earth, and thereby alter natural erosion rates (Toy & Foster 1998) causing soil degradation and constituting important non-point source for pollution of water bodies and impact to aquatic ecosystem (Rompaey & Dostal 2007). Erosion occurs when soil is left bare and exposed to erosive agents (Foster *et al*. 2003). Soil erosion caused by rainfall and its associated overland flow encompassed detachment, transportation, and deposition process (USDA 2008). For most of the soil types, a soil loss tolerance threshold of 10 ton/ha/year is typically used (Renard *et al*. 1997).

Four major factors affect soil erosion: climate, soil, topography, and land use. Rainfall drives erosion according to its intensity (how hard it rains) and amount (how much it rains). Temperature and precipitation together determine the longevity of biological materials like crop residue and applied mulch used to control erosion. Soil types differ in their erodibility, thus the basic soil properties such as texture and organic mater content provide an indication of erodibility. Slope length, steepness and shape are the topographic characteristics that most affect erosion and deposition. Finally, land use is the single most important factor affecting soil erosion and it is strongly enhanced by the human activities. Vegetative cover greatly reduces soil loss. Two types of practices are used to control soil loss: cover-management (cultural) practices including vegetative cover, crop rotations, conservation tillage and applied mulch (Foster *et al*. 2003), and supporting practices, which include ridging (e.g. contouring), vegetative strips and barriers (e.g. buffer strips, strip cropping, fabric fence, gravel bags), runoff interceptors (e.g. terraces, diversions) and small impoundments (e.g. sediment basins, impoundment terraces). These practices reduce erosion primarily by reducing the erosivity of surface runoff and by causing deposition (USDA 2008).

Erosion and sediment transportation have been studied a lot for modeling purposes (Quinton 2004). Several models have been developed: Universal Soil Loss Equation (USLE) (Wieschmeier & Smith 1978), Revised Universal Soil Loss Equation (RUSLE) (Renard *et al*. 1997), Morgan-Morgan-Finney (MMF) (Morgan *et al*. 1984, Quinton 2004), Soil and Water Assessment Tool (SWAT) (Netsch *et al*. 2005), Water Erosion Prediction Project (WEPP) of National Soil Erosion Research Laboratory - USDA-ARS-MWA (Flanagan & Nearing 1995), among several others. A model of erosion and sedimentation process, even the most complex one, is only a representation of reality; the full reality can never be reached (Quinton 2004). Determining the input for soil-erosion is difficult. Input parameters vary in time and space, and some are difficult to measure (Quinton 2004). It induces a considerable level of uncertainty. For example, considerable variation between similar sites exposed to the same rainfall has been reported (Catt *et al*. 1994, Quinton *et al*. 2001, Quinton 2004). Increasing the number of processes represented in soil-erosion models for a more complete description of the erosion process, and thereby the number of inputs to the model, will not typically lead to a better prediction of erosion and sedimentation than the simple models (Quinton 2004). Therefore, a simple way to simulate erosion and sedimentation with reliable data and consistent models could be worthy.

Several comparisons between simple and complex erosion models have been carried out, for example Morgan and Nearing (2000), cited in Quinton (2004), compared the performance of the USLE, RUSLE and WEPP using 1700 plot years of data from 208 natural runoff plot, and reported that the complex physical-based WEPP model didn't perform better than the empirical models USLE and RUSLE. Because the RUSLE takes into consideration all major components likely to affect rill and interrill erosion, it is the most widely used soil loss equation (Mathews *et al*. 2007).

Since the discovery that erosion is linearly proportional to storm erosivity, the development of the Universal Soil Loss Equation (USLE) has been facilitated (Foster *et al*. 2007). USLE has followed a continuous development. It was first published in 1958 (USDA Agriculture Handbook 282) and the refined and improved in 1978 (Agriculture Handbook 537). Williams (1975) and Williams & Berndt (1977) modified the USLE equation to estimate stream sediment yield for individual storms with its rainfall factor (R) replaced by a runoff factor and called it the modified universal soil loss equation (MUSLE) (Sadeghi *et al*. 2007). In 1980 Dissmeyer & Foster extended USLE application on forest land. Then, the USDA released the Revised USLE (RUSLE) version 1 in 1992. It was periodically upgraded to RUSLE1.06 (1998) and later on to RUSLE1.06c (2003) which extended its applicability to mined land, construction sites, and reclaimed lands (Toy & Foster 1998). Finally in 2005 RUSLE2 was released.

RUSLE predicts long-term values (effects of sub-processes are lumped) as a function of erosivity (forces applied to the soil by the erosive agents) and erodibility (susceptibility of the soil to erosion) factors using the following mathematical equation

$$A = RKLSCP \tag{7}$$

where A = average annual soil loss (t/(ha/year)), R = rainfall/runoff erosivity factor ((MJ mm)/(ha h)), K = soil erodibility factor ((t/ha)/(MJ mm)), L = slope length factor, S = slope steepness factor, C = cover management factor, and P = supporting practices factor. A summary of the factor calculation equation is presented in Table 7 of the appendix. A detailed explanation of the factor calculations is given in, e.g., Renard *et al*. (1997), Toy (1998), Foster *et al*. (2003), and USDA (2008).

Where no rainfall data are available to compute the R value for a given location, an estimate of R may be obtained based on a vicinity base station where R is known using the relation (8) (Toy 1998):

$$R_{new} = R_{base}\,(P_{new} / P_{base})^{1.75} \tag{8}$$

where R_{new} = the new value for R at the desired new location, R_{base} = R value computed by standard methods at a base location, P_{new} = the average annual precipitation at the new location, and P_{base} = the average annual precipitation at the base location.

The method developed by Moore & Burch (1986a,b) given in Equations (9) and (10) is used for calculating the slope length factor (L) and slope steepness factor (S) from the Digital Elevation Model (DEM) in most of GIS systems (Lim *et al*. 2005). The length of hill slopes in the USLE experimental plots ranged from 10.7 m (35 ft) to 91.4 m (300 ft). Thus, it is recommended the use of slope lengths less than 122 m (400 ft), because overland flow becomes concentrated into the rills in less than 122 m (400 ft) under natural condition (Foster *et al*. 1996, Lim *et al*. 2005).

$$LS = (A / 22.13)^{a} * (\sin\theta / 0.0896)^{1.3} \tag{9}$$

or

Pow([Flowaccumulation] * cellsize / 22.13, a)*(Pow(sin([Slope in Degree] / 0.0896, 1.3) (10)

where A = Flow accumulation * cell size, θ = Slope angle in degrees; a = 0.4 if gradient < 9 % and 0.6 if gradient > 9%.

While RUSLE has great practical value, its limitations should be recognized. The main limitations of the RUSLE are that 1) it does not provide explanation of the effects of the sub-processes involved on soil erosion, i.e. effects of annual variation runoff, soil moisture and evapotranspiration; 2) It only predicts sediment entrained in the erosion process but doesn't predict sediment yields into particular basins; 3) It predicts average annual soil loss but does not provide annual soil loss distribution according to the precipitation occurrence neither predict soil loss in a particular storm event (later version, RUSLE2 does calculations for a single storm event); 4) It is effective for erosion through sheet and rill flow only on short slopes (<300 ft) and not for concentrated flow or long slopes; 5) It does not adequately take into account soil dispersibility in assessment of the K-factor (Mathews *et al*. 2007). Caution should be taken into account in areas where processes of gully and channel erosion are present. These can contribute more than 50% of the sediment produced (Blong 1985, Quinton 2004).

Other things to consider, which can induce error into the model output, are type and scale of input data being used. GIS and Environmental models usually use as inputs widely available data sets which are generated in different types (single events, multiple event, short-term and long term historic data) and scales (plot scale, hillslope, farm, field, watershed, regional), which involve a sequence of information transformation called scaling steps (Renschler 2000). This requires further spatial accuracy assessments.

Soil erosion studies in Andean region are still scarce, even though the soil degradation rates in the Andes are high. Peru is one of the Andean countries exhibiting different stages of the problem of erosion (Amezquita *et al*. 1998, Romero León 2005). The main causes of erosion are intensive land use, overgrazing of pastures, cultivation of annual crops on steep slopes, deforestation, built-up areas, roads and abandoned land (Stroosnijder 1997, Romero León 2005). Insufficient attention has been given to elucidating the factors that affect the soil erosion processes (Romero León 2005). Understanding the erosion process is not easily obtained in a cultural and physical environment as diverse and complex as the Andes, particularly given the paucity of experiment and data needed to quantify soil erosion for the variety of land use systems in the region (Bowen *et al.* 1997).

RUSLE model was developed and calibrated in different conditions (of climate, slope, topography, soil and land use and management) than Tropical Andes. For example, the LS factor have been derivated from experimental plots with slopes no more than 5^o (9%) and lengths of 22.1m, which is different than in the Andes, where most of the soil is located on slope more than 22^o. Even slopes of 65^o are found and slope lengths of more than 100m. The K factor calculation had a threshold of a maximum level of 4% of organic matter, while the tropical soil may largely exceed this threshold. And the C coefficient in the Andes differs due to the type of crops, cover, homogeneity of sowing and harvest from the documented RUSLE C database. The RUSLE C factor calibration relates to a good managed pasture, which is different from the tropical Andes where most of the pastures are overgrazed and scarce. For these reasons the RUSLE application in the Tropical Andes induces biases, which usually cause overestimation of the soil loss (FAO 1993).

Saavedra & Mannaerts (2005) tested five erosion models (USPED, USLE, RUSLE-3D, SPL and MMMF) with modest data input requirements in Bolivian semi-arid mountains, to overcome the data limitations which are a common limitation in Bolivia and the rest of the Andean region. The results of the models were validated with remote sensing imagery, which provides a spatially explicit background for indirect model validation overcoming the lack of erosion measurements to model calibration and validation. The model validation showed that none of the five models accurately predicts soil erosion across the catchment. It is therefore concluded that although the spatial patterns of predicted erosion by the different models seem reliable, quantitative prediction should be interpreted with caution. Their practical utility is based upon providing means for evaluating and comparing erosion factor changes among alternative land areas, besides a prediction of the absolute soil erosion for a particular location can be obtained (Saavedra & Mannaerts 2005).

A large amount of sediment yield (the amount of sediment reaching downstream areas) from a certain watershed over an average year is usually a sign that the condition of the watershed is degrading (Lane *et al*. 2001, Blaszczynski 2003). The input of sediment by erosion processes into reservoir, channels, drainage channels, etc. determine the performance and their lifetime (Lane *et al*. 1997). A high sedimentation rate in rivers, lakes, reservoirs and ponds affect the aquatic ecosystem functioning through modifying the hydraulic morphology and water quality (Kinnell 2008) and increase the risk of flooding (Rompaey & Dostal 2007).

As RUSLE is a field scale model, it cannot be directly used to estimate sediment yield, because some portion of the eroded soil may be deposited while traveling to the watershed outlet, or the downstream point of interest. To account for these processes, the Sediment Delivery Ratio (SDR) for a given watershed should be used to estimate the total sediment transported to the watershed outlet (Lim *et al*. 2005). The SDR is expressed as:

$$SDR = SY/E \qquad (11)$$

where SDR = Sediment Delivery Ratio, SY = Sediment Yield, and E = gross Erosion for entire watershed. It can be noted that gross erosion (E) includes the erosion from gully and channel erosion as well as rill and interrill erosion (Ouyang & Bartholic 1997, Lim *et al*. 2005). As it was mentioned above, gully and channel erosion could be responsible for more than 50% of sediment production in a catchment (Blong 1985, Quinton 2004), and thus the RUSLE result obtained from the calculation of the sediment yield in a basin should be taken with caution. It can only be valid if there is no significant erosion occurring from the gully and the channel processes (Lim *et al*. 2005).

Several methods have been developed to estimate SDR. Lu *et al*. (2004b) grouped them in three general categories: The first category contains methods for situations where sufficient sediment yield and stream flow data are available from the specific site, such as sediment rating curve-flow duration (Gregory & Walling 1973, Lu *et al*. 2004b), or reservoir sediment deposition survey. However, such approaches are not suitable for estimating the spatial distribution of sediment yield for a large basin because the measurement results required are rarely available from all catchments. The second category uses empirical relationships which relate SDR to the most important morphological characteristics of a catchment, such as the area of the catchment (Roehl 1962, Lu *et al*. 2004b). A widely used method is to calculate a power function of the area:

$$SDR = \alpha A^{\beta} \tag{12}$$

where A = catchment area (in km^2), α and β are empirical parameters. Statistical regression model based sediment measurements have revealed that the exponent β should be in the range from –0.01 to –0.25 (Walling 1983, Lu *et al*. 2004b). The power functions developed by Vanoni (1975), Boyce (1975) and USDA (1975) (Equations 13, 14 and 15 respectively) belong to this category. They have been derived from the data collected from 300 watersheds and the goal has been to develop a generalized SDR curve (Lim *et al*. 2005).

$$SDR = 0.4724\ A^{-0.125} \tag{13}$$
$$SDR = 0.3750\ A^{-0.2382} \tag{14}$$
$$SDR = 0.5656\ A^{-0.11} \tag{15}$$

where A = watershed area (km^2) and the resulting SDR values range from 0 to 1. Small watersheds get high values; meaning that most of the eroded soil moves to the downstream areas without significant deposition. SDR value decreases as the size of the watershed increases (Lim *et al*. 2005).

Despite its simplicity, according Lu *et al*. (2004b), Equation 12 provides little understanding about the mechanism that cause sediment transport (the physical process) and fails to identify the separate effect of climate (e.g. erosive rainfall) and catchments condition (e.g. vegetation, topography, and soil properties) and their complex interaction in a large basin.

The methods belonging to the third category of SDR estimation attempt to build models based on fundamental hydrologic and hydraulic processes, in most of which the sediment delivery and deposition are predicted through the coupling between runoff and erosion/deposition conditioning upon sediment transport capacity (Flanagan & Nearing 1995, Lu *et al*. 2004b). Despite the merit of physical description, the existing models are often not suited to basin scale applications.

4 Materials and Methods

4.1 Study Area

The study area is the Huatanay watershed (490 Km^2), located in the Tropical Andes of Peru, region of Cusco, at 71°51’13” and 13°33’48” (Figure 2) with a mean temperature of 12 °C and total annual precipitation of 665 mm. The main watershed collector is the Huatanay river, with a 7.5 m^3/s as an average maximum discharge (February) and 1.1 m^3/s as an average minimum discharge (August) (IMA 1994). The Huatanay River is highly contaminated, due to urban domestic and industrial waste water discharges and accumulation of solid residues along river banks being the main pollutant sources. These pollutants affect the physical, chemical and biological properties of the river strongly. The main urban area in the watershed is Cusco, the former capital of the Inca empire. Most of the main urban areas have developed on the floodplain valley along the regional road Cusco – Puno (Saji Carcagno *el al*. 2005), constrained by the geomorfological characteristics of the watershed (Carazas Aedo 2001).

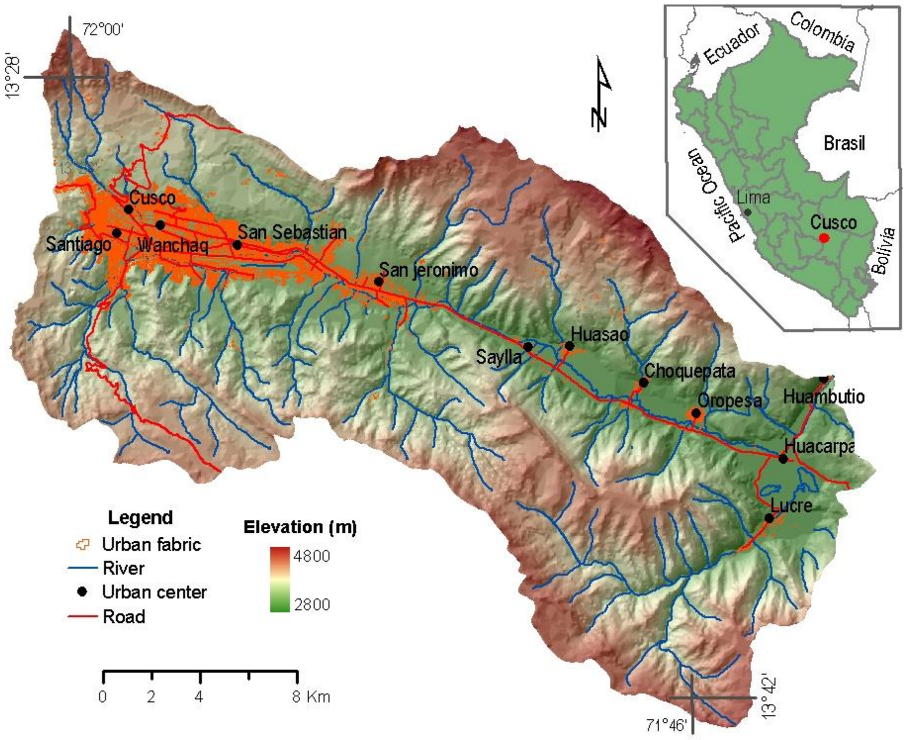

Figure 2. Huatanay Watershed Ubication

The population of the Huatanay watershed was 352,474 inhabitants in 2005 (INEI 2005), increasing 2.4 times from the population size registered in 1972 (147,503 inhabitants) (INEI 1972). The urban area represents 86 per cent (302,476 inhabitants) of the total population in the Huatanay watershed.

The main economic activities at the Huatanay watershed which employ the economically active population are: services and tourism (37%), commerce (31%), manufacturing (17 %), and agriculture (4%) (IMA 1994). The tourism is an important economic sector in the Cusco region, linked with hotels, restaurants, transport and travel agency services. In 2007 1,401,444 tourists were registered (DIRCETUR-GRC 2007), increasing 794 % from 1991 (176,454 tourists) (DIRCETUR-GRC-DRIT 2007). Several archaeological sites of pre-Inca, Inca and colonial builds are located in Cusco region, e.g. Machupicchu, and a valuable natural mountain environment.

The Huatanay watershed is a typical Andean mountain environment with diverse ecosystems. The Andean mountains are characterized by the major eco-climatic heterogeneity by unit of area in the world due to abrupt change in elevation and the North-South position of mountain chain, which act as a barrier cutting down the main atmospheric circulation and the effects on the regional weather of the pacific ocean circulation pattern (southern oscillation), generating considerable differences in macro and micro climate between the western and eastern slopes and surrounding lowlands (Earls 1992, Torres Guevara 1999). Due to the wide latitudinal range and altitudinal variability, Andes are biologically a very diverse area. However, Killeen *et al* (2007) remark that the wind patterns and topography are responsible for creating the precipitation patterns that define the natural ecosystems of the region hypothesizing that the distribution of plant species on the eastern slope of the Andes and adjacent regions of the western Amazon is constrained by precipitation gradients that are independent of latitudinal gradient. Because of high exposure to wind and rain, the mountains are subject to harsh environmental conditions. In addition, due to the varying rainfall conditions, the seasonality of dry and wet periods (Torres Guevara 1999) and the anthropogenic impact, the Andes are considered to be a fragile environment, where most of the processes are still poorly studied (Fjeldså & Kessler 2004). A remarkable characteristic of Andes agro-ecosystems is a rapid decline in biological production, due to the intensification of agricultural production exceeding the natural homeostasis of the Andean environment, the introduction of alien species, and inappropriate cultivation technologies.

Thus, the applied paradigm of development should not lead to conventional mercantile competitive economic production (Torres Guevara 1999). Instead, an efficient management of the Andean mountain area could be achieved by taking into account the complexity of the ecosystem and by creating a production system based on ecosystem functions (Torres Guevara 1999).

4.2 Dataset

The principal data used in this thesis were: Landsat Thematic Mapper (TM) satellite images corresponding to the path 004 and Row 069, from the years 1988, 1998 and 2007. They were free on-line images provided by the Brazilian National Institute of Spatial Research (INPE). The image spatial resolution (pixel size) is 30 m, and the images have seven bands. The images were cloud free in the area that corresponds to Huatanay river basin.

The Peruvian topographic base maps were also used, with a scale of 1/100,000 and contour line equidistance of 50 m, corresponding to the sheets 27-r, 27-s, 28-r and 28-s. They have been created by the National Geographic Institute of Peru and were provided in ESRI shapefile format. Other spatial information surveyed by local institutions have also been used: Rural Cadastres (Special Project of Land Titling and Rural Cadastre of Peru - PETT), Urban Cadastre (Municipal of Cusco), Soil Maps (Institute of Water and Environment Management – IMA-Region Cusco), Geological Maps (Institute of Geological, Mine and Metallurgical of Peru - INGEMMET). Meteorological data was provided by the National Service of Meteorology and Hydrology of Peru (SENAMHI), and some other data reviewed from the literature sources.

Additionally, interviews for the local farmers and authorities were carried out in 2006 to characterize the type of agricultural production and land cover management practices in each LCLU class, which were used to estimate the cover management factor (C factor) in RUSLE erosion model. And GPS points were collected in different LCLUs as a ground truth for image classification evaluation.

4.3 Data Processing and Analysis Methods

Each image (1988, 1997 and 2007) was geo-referenced and ortho-corrected using the basic topographic maps and a generated Digital Elevation Model (DEM) of the study area. Since the Landsat TM images are affected by haze, a radiometric correction was accomplished using the ERDAS algorithm of Haze reduction. In addition, because the images correspond to mountainous region and often contain a radiometric distortion for topographic effect, topographic normalization was attempted using the Lambertian reflectance models (Algorithm available in ERDAS Imagine 9.x). However, this normalization induced a lot of alteration on the original image spectral characteristic and therefore was not used. To overcome the topographic effect, the mountain shaded areas in the images were masked and classified separately.

The images were classified using a combination of supervised and unsupervised classification. Unsupervised classification was used to generate the basic set of classes taking into account the spectral characteristics of the image. Then, each class was recognized using secondary information (previous land cover map, cadastre, high resolution images and field information) and attaching the class meaning. And finally, supervised classification was performed, based on the result of the unsupervised classification. Areas which had a good spectral clustering in unsupervised classification and represented the recognized classes in the field were taken into account when creating the signatures for the classes. The signature evaluation was performed using the transformed divergence statistical method. The classes' assignment was performed using the Maximum likelihood methods. In order to reduce isolated pixels and improve map representation, a post-classification processing was accomplished using the fuzzy convolution techniques and the distance error image file generated by the maximum likelihood classification (algorithm available in ERDAS Imagine 9.x). The accuracy of the classification was evaluated with an error (confusion) matrix and the kappa index, using GPS field collected points, a high resolution image from Google Earth and other ancillary information (rural and urban cadastre).

Using the LCLU map generated for the years studied, the LCLC change analysis has been performed using the following techniques: Cross-tabulation, Cross-classification, Kappa Index of Agreement, Area losses and gains evaluation of each LCLU classes, and net change contribution and persistence analysis (using the Land change Modeler algorithm available in Idrisi). The RUSLE soil erosion model was used to estimate the soil loss and the RUSLE factor generation process is presented in the results and discussion.

In order to analyze the effects of Land cover and Land Use Change on soil loss, two factors have been taken into account: Land Cover and Land Use (from the years 1988, 1997 and 2007) and terrain slope (six slope classes). Because the obtained data by modeling is not normally distributed (Kolmogorov-Smirnov test, $p = 0.001$), a non-parametric Friedman test was performed in order to find out, if the detected land cover / land use change had an effect on soil loss rate.

The GIS-based Sediment Assessment Tool for Effective Erosion Control (SATEEC) algorithm, created with ESRI avenue language (Lim *et al*. 2005), was used to model the sediment yield in the Huatanay watershed. SATEEC is based on the RUSLE estimated soil loss and a spatially distributed Sediment Delivery Ratio (SDR) map, which are needed to be able to account the deposition and transportation of the eroded soil. Vanoni (1975) function was used to estimate the SDR. The computed SATEEC result is a "Sediment Yield" map, where each cell value represents the total amount of sediment yield for each watershed having each cell as an outlet. It also reports a map of sediment yield and the amount of sediment yield delivered at the outlet of the watershed.

5 Results and Discussion

Land Cover and Land Use Multi-Temporal Maps

Three Landsat images related to the study area were processed. They had geometric correction root mean square errors (RMSEs) of 1.65, 1.31, and 1.95 for the 1988, 1997 and 2007 images respectively. The supervised classification was performed to nine classes: Forest land, Scrubland, Pasture, Seasonal cropland, Irrigated cropland, Barren land, Wetland, Lake, and Built up land. The signature samples evaluation (transformed divergence statistic) gave a good separability for the classes (>1700; see the results in the appendix Tables 1 to 6). For the shade masked images (without shade) the best average separabilities were 1963.86, 1935.23, 1981.55 in 1988, 1997 and 2007 respectively, and similarly, the best minimum separabilities for those images were 1730.59, 1720.73, 1907.3. For the images under shade the best average separabilities were: 1983.27, 1961.33, and 1981.96 in 1988, 1997, and 2007, and the best minimum separabilities were: 1939.94, 1768.12, and 1942.23.

The error matrix result for classification accuracy evaluation for the 2007 classified image are presented in Table 1. 144 ground points of verification were used. The general kappa index obtained is 0.82, which implies that the classification process is avoiding 82 percent of the errors that a completely random classification would generate. For the classified images of 1988 and 1997 the classification accuracy was not evaluated, because no sources of verification have been found for these years.

Table 1. Error matrix of Land Cover and Land use Classification (2007), Huatanay Watershed, Cusco, Peru.

Class	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	Total	Number correct	User's accuracy (%)	Kappa
Forestland (1)	14	0	0	0	0	0	0	0	0	14	14	100.0	1.00
Scrubland (2)	0	6	0	0	2	0	1	0	0	9	6	66.7	0.65
Pasture (3)	0	0	10	0	0	0	0	0	0	10	10	100.0	1.00
Barren land (4)	0	1	1	11	0	0	0	0	5	18	11	61.1	0.58
Seasonal cropland (5)	1	1	0	1	16	3	0	0	0	22	16	72.7	0.68
Irrigated cropland (6)	0	0	0	0	1	29	0	0	2	32	29	90.6	0.88
Wetland (7)	0	0	0	0	0	0	6	0	0	6	6	100.0	1.00
Lake (8)	0	0	0	0	0	0	0	5	0	5	5	100.0	1.00
Built up land (9)	0	0	0	0	2	1	0	0	25	28	25	89.3	0.86
Total	15	8	11	12	21	33	7	5	32	144	122		
Producer's accuracy (%)	93.3	75.0	90.9	91.7	76.2	87.9	85.7	100.0	71.1	Overall		84.72	0.825

The final classified images are presented in Figure 3, and the classes' descriptions are given in the following paragraphs.

The Forest land is composed of both native and introduced species. The native species are present in reduced isolated areas dominated by the species: *Escallonia resinosa* (Chachacomo), *Escallonia myrtilloides* (T'asta), and in less proportion: *Alnus acuminate* (Aliso) and *Polylespis spp* (Queña) (GPA 2004). The introduced species are dominated by the *Eucalyptus globulus* (Eucalipto), which represents the largest forest extension on the watershed. These trees have been planted in the area since 1960 (IMA 1994).

The Scrubland, located on relatively dry and very steep slopes characterized by spiny woody vegetation, is dominated by the species: *Baccharis buxifolia* (Tanyanca), *Colletia spinosissima* (Roque), *Barnadesia horrida* (Llaulli), *Senna vargasiil* (Mutuy), *Berberis boliviana* (Checche) (GPA 2004), *Baccharis chilco* (Chillca) (IMA 1994). These species are in intensive use for fuel. Their spatial cover has also been altered by fire (IMA 1994).

The Pasture contains a diversity of species communities, mainly dominated by the associations: *Festuca rigidifolia – Muhlenbergia peruviana; Scirpus rigidus – Plantago sp.; Stipa ichu* (Ichu) - *Stipa obtusa* - *Festuca rigidifolia*; *Calamagrostis amoena – Muhlembergia peruviana; Festuca ortophylla* (Iru); *Festuca dichophylla – Muhlenbergia peruviana;* and *Scirpus rigidus – Muhlenbergia fastigiata* (GPA 2004).

Seasonal cropland, where the crop depends only on the seasonal rainfall (September – April), is dominated by the following crops: *Solanum andigenum* (native species of potatoes) , *Oxalis tuberose* (Oca), *Ollucus tuberosus* (Olluco), *Tropaeolum tuberosum* (Mashua), *Triticum spp.* (Wheat), *Hordeum vulgare* (Barley), *Vicia faba* (Broad Bean), and *Lupinus mutabilis* (Tarwi) (GPA 2004). This class includes also the rotational cropland areas (Muyu-muyu or Layme), located at the highest lands of the watershed. These croplands are cultivated during 3-5 years and then relocated to another area for the same period. The used areas are left for nutrient recovering and natural pasture use for several years (Tapia 2000). The cycling period to returning to the same area depends on the land extension available for the local community and on the number of community members.

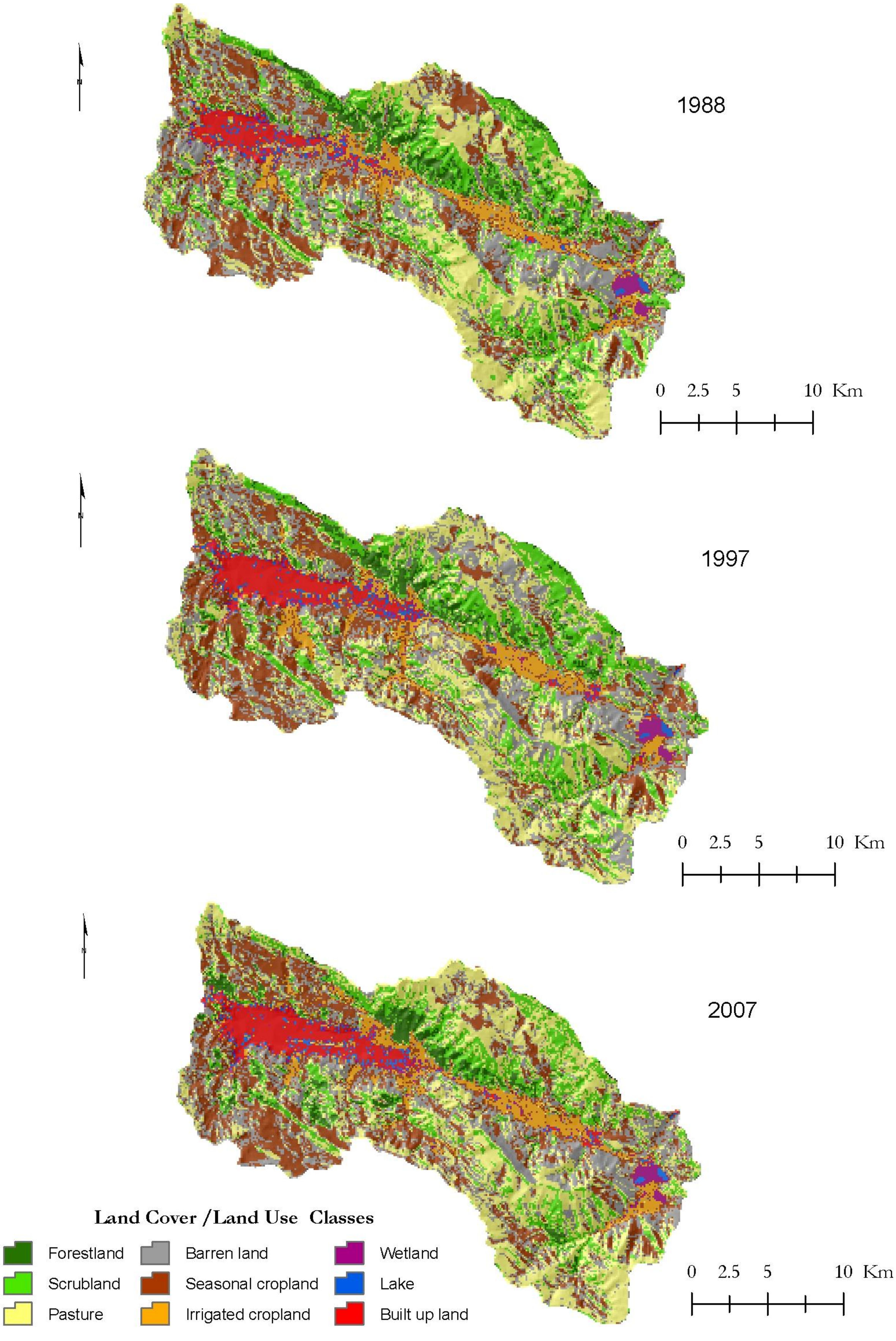

Figure 3. Classified Land Cover and Land Use (LCLU) Maps using Landsat TM satellite images for Huatanay Watershed, Cusco Peru.

The Irrigated cropland is mostly located on the floodplain of the watershed; it encompassed mainly vegetable crops: *Pisum sativum* (Peas), *Solanum tuberosum* (Potatoes), *Zea mays* (Corn), *Triticum* spp. (Wheat), *Hordeum vulgare* (Barley). Barren land encompasses the thin soil areas, river sand areas, exposed rock, and low and scarce vegetated lands. And finally, Built up land class encompasses the urban fabric, suburban construction areas and archaeological areas.

Land Use Change Analysis

For each classified image the area of each LCLU class was computed (Table 2) and compared statistically if there are differences between the images.

Table 2. Area of Land Cover and Land use Classes by Year (in hectares and percent), Huatanay Watershed, Cusco, Peru.

	Classes	1988	%	1997	%	2007	%
1	Forestland	6647	13.6	4672	9.5	3922	8.0
2	Scrubland	8731	17.8	9217	18.8	8560	17.5
3	Pasture	9721	19.8	10517	21.5	11790	24.1
4	Barren land	10203	20.8	9043	18.5	8135	16.6
5	Seasonal cropland	8764	17.9	9877	20.2	10089	20.6
6	Irrigated cropland	2722	5.6	2666	5.4	2894	5.9
7	Wetland	283	0.6	297	0.6	288	0.6
8	Lake	72	0.1	53	0.1	64	0.1
9	Built up land	1861	3.8	2660	5.4	3260	6.7
	TOTAL	49003	100	49003	100	49003	100

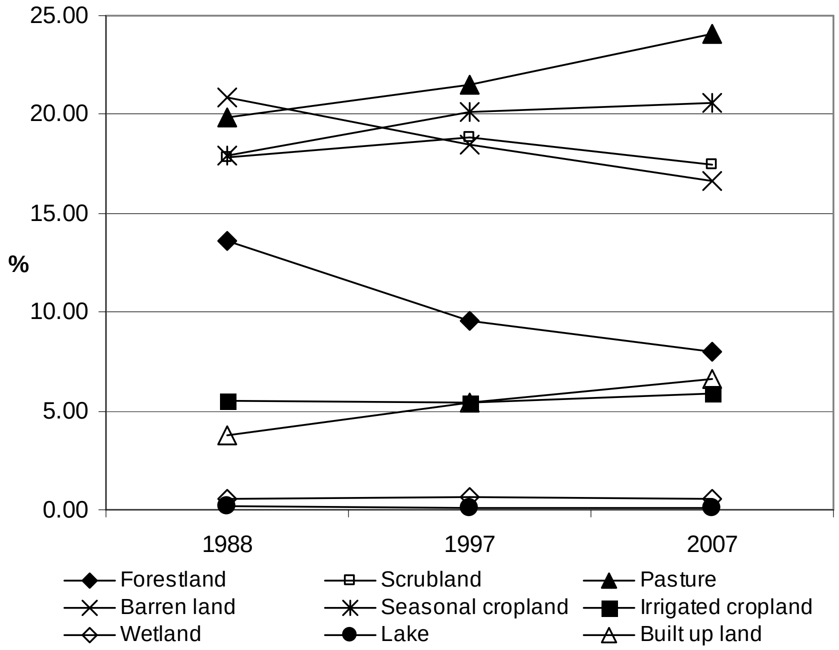

Figure 4. Land Cover and Land Use Change within 1988-2007, Huatanay Watershed, Cusco, Peru.

Table 2 and Figure 4 show changes in area (increasing or decreasing) for most of the classes. Forestland and Barren land have clearly decreasing trends while Pasture and Built up land have clearly increasing trends. The other classes show slight changes.

A cross tabulation and cross-classification of the LCLU map of 1988 against 1997 and 1997 against 2007, gave an overall kappa index of agreement of 0.41 and 0.40 respectively, revealing a low agreement between the images, and change occurrence can be assumed between the LCLU classes in the period studied. Table 3 shows a summary of Kappa Index of Agreement by classes. Appendix Tables 7 and 8 show the results of the cross tabulation.

Table 3. Kappa Index of Agreement values per class (KIA), calculated from the cross tabulated tables (Tables 7 and 8 in the appendix). Huatanay Watershed, Cusco, Peru.

	Classes	1988-1997	1997-2007
1	Forestland	0.40	0.33
2	Scrubland	0.48	0.47
3	Pasture	0.41	0.35
4	Barren land	0.20	0.19
5	Seasonal cropland	0.41	0.38
6	Irrigated cropland	0.55	0.57
7	Wetland	0.87	0.85
8	Lake	0.68	0.93
9	Built up land	0.90	0.88
	Overall Kappa	0.41	0.40

In most of the classes the change from 1988 to 1997 and from 1997 to 2007 is evident (a low kappa value per class), except the Wetland, Lake and Build up land which have values near to 1. The areas of these classes are more stable during the study period and no relevant change of those classes to other classes can be perceived.

The land use change assessment by evaluation of gains and losses by classes, net change, and persistence are presented graphically in Figures 5 to 14. The analyzed periods of 1988-1997 and 1997-2007 confirm the high dynamic state of the watershed landscape. Most of the classes have gains and losses, with the exception to Built up land, whose losses are negligible. A threshold of 200 ha was set for distinguishing a significant change to avoid errors in image classification due to the dynamic nature of defining the classes.

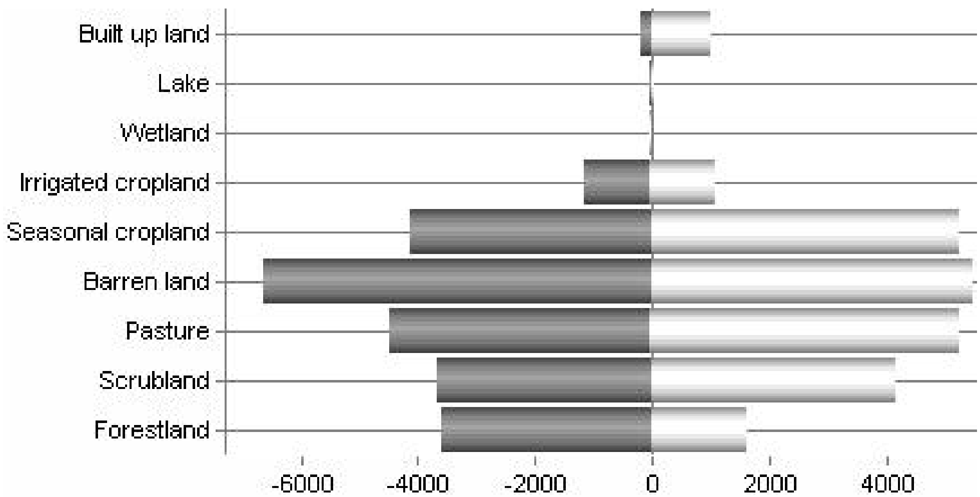

Figure 5. Gains and Losses of LCLU categories between 1988 – 1997 (ha), Huatanay watershed, Cusco, Peru.

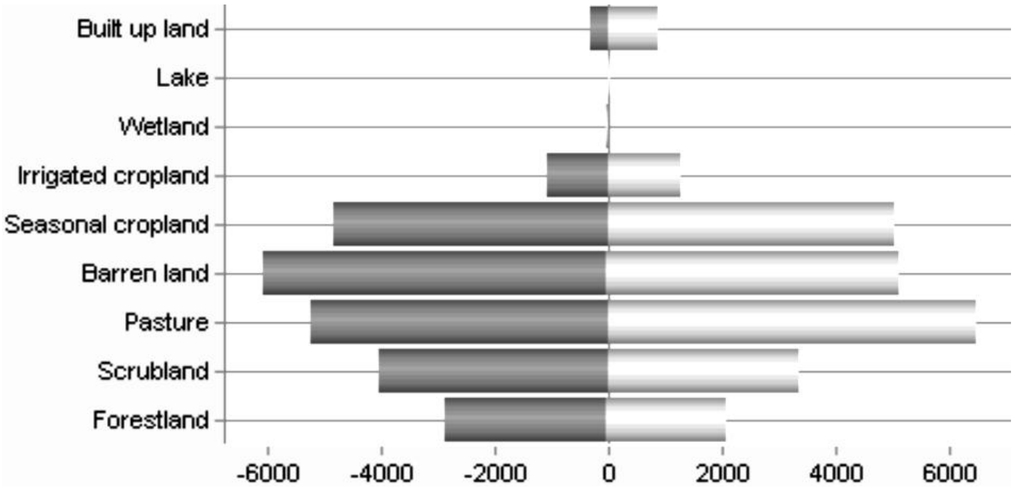

Figure 6. Gains and Losses of LCLU categories between 1997 – 2007 (ha), Huatanay watershed, Cusco, Peru.

For example, in the period from 1988 to 1997, Barren land has been lost 6651 ha (65.2 %) and has been gained 5490 ha (60.7 %), with a net loss of 1161 ha. And in the 1997-2007 period it has been lost 6098 ha (67.4 %) and gained 5190 ha (63.8 %), with a net loss of 908 ha Forestland has been lost 3581 ha (53.9%) and gained 1606 ha (34.4 %) in 1988-1997 with a net loss of 1975 ha (29.7 %). In the 1997-2007 period the loss was 2880 ha (61.6%) and the gain 2129 ha (54.3 %) with a net loss of 750 ha.

Built up land gained 983 ha (37 %) in 1988-1997 and 901 ha (27.6 %) in 1997-2007. Also some losses can be perceived, but they are not taken into account due to a threshold of 200 ha.

Similar trends are shown for the rest of classes, with exception of Wetland and Lake, which seem to be stable.

A net change contribution analysis tracks in detail the LCLU classes; from which class the gained area have come and to which class they have gone, giving a complete picture of the dynamic state of the LCLU classes. The analysis for Barren land, Seasonal cropland, Forest land and Built up land are given in Figures 7 to 14.

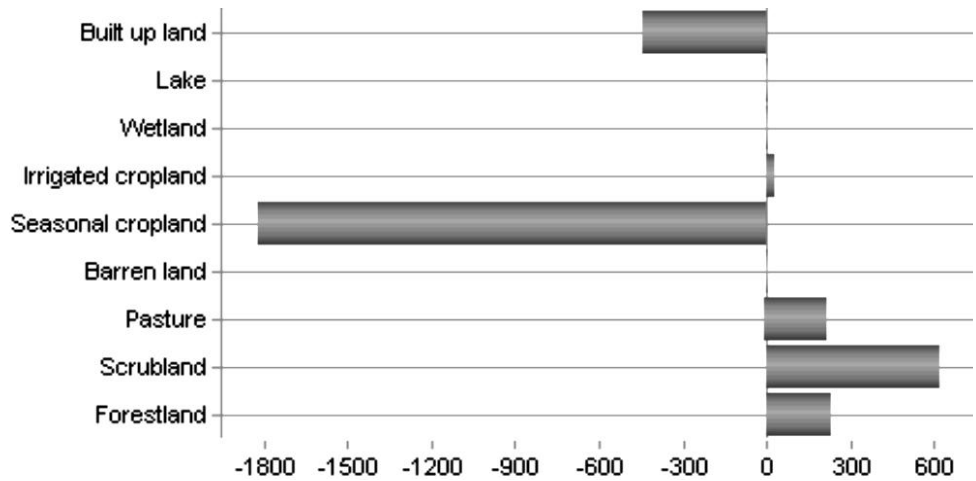

Figure 7. Contribution to the net change in Barren land (1988-1997) (ha), Huatanay watershed, Cusco, Peru.

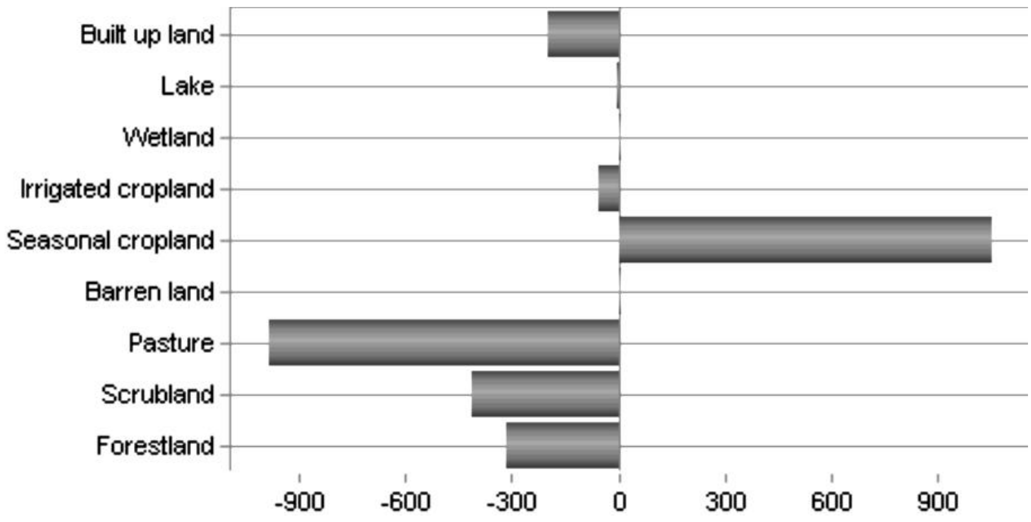

Figure 8. Contribution to the net change in Barren land (1997-2007) (ha), Huatanay watershed, Cusco, Peru.

Analyzing the graphs of contribution to the net change in Barren land in 1988-1997, it can be noticed that the Barren land has lost area mainly to Seasonal cropland class (1822 ha) and a minor proportion to Built up land (443 ha), and it has gained area from Scrubland (8623 ha), Forestland (231 ha) and Pasture (224 ha). In 1997-2007, most of the losses in the Barren land went to Pasture (989 ha), Scrubland (410 ha), Forest land (314 ha) and Built up land (199 ha), and most of the gain is obtained from Seasonal cropland.

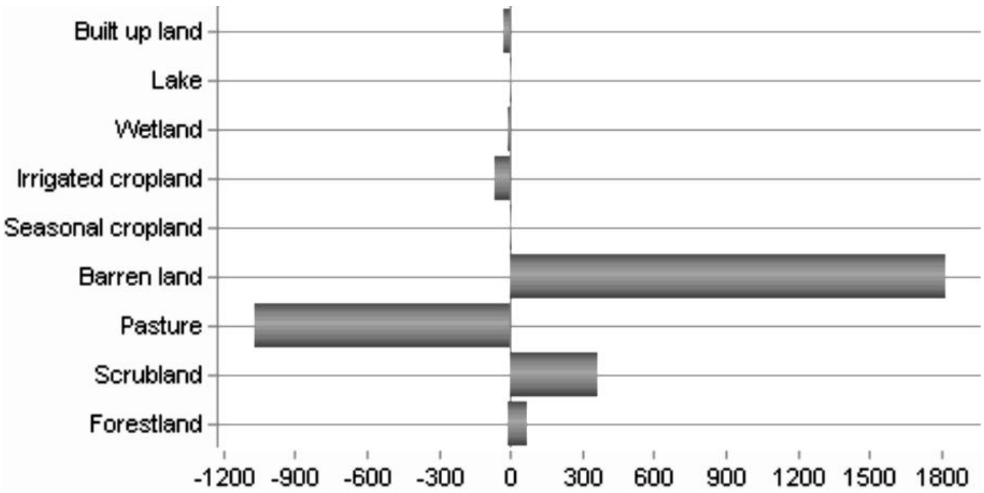

Figure 9. Contribution to the net change in Seasonal cropland (1988-1997) (ha), Huatanay watershed, Cusco, Peru.

In the net change in Seasonal cropland class in 1988-1997 the main contributor for the area gain was the Barren land class (1822 ha), and a small proportion came also from the Scrubland (367 ha). The main area losses went to Pasture class (1070 ha).

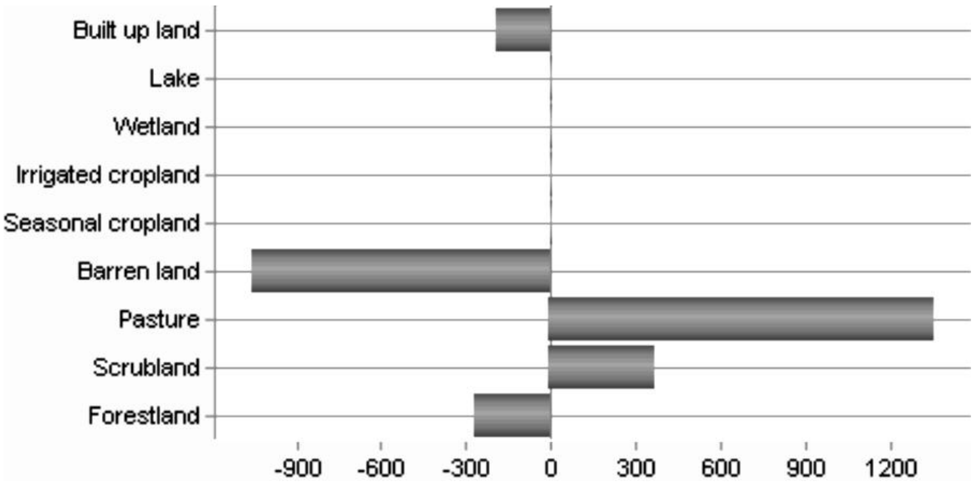

Figure 10. Contribution to the net change in Seasonal cropland (1997-2007) (ha), Huatanay watershed, Cusco, Peru.

In 1997-2007 the main contributor to the area gain in Seasonal cropland class is the Pasture (1365 ha), and a minor contributor is the Scrubland (372 ha). Seasonal cropland has lost area mainly to Barren land (1060 ha) but also to Forest land (269 ha) and Built up land.

For the changes in both LCLU classes analyzed above (Barren land and Seasonal cropland) several reasons can be given. First, the Seasonal cropland is rotating systems, where land is used for a crop production and then left for recovery for a certain period. During the recovery it can stay as a bare soil and then pass to Pasture or to Scrubland as a natural succession. Secondly, most of the Pastures and Scrubland are still under the effect of fires practised either to facilitate the farming work before the cultivation or to renew green pasture for livestock grazing. Third, some pasture areas with declined vegetation cover due to overgrazing, may be recognized as Barren land in the next period, or the vegetation cover of Barren land can be recovered and the class changed to Pastures. Fourth, the Scrubland is used as fuel, and consequently local residents cut the Scrubland for fuel and modify very often its extension. Fifth, some changes can represent as an error in image classification, since there are difficulties to separate adequately the Seasonal cropland, Barren land and Pasture in some areas, depending on the conditions of the class and the season. Even though the images used in this study belong to the same season (dry), some differences in vegetation phenology can be observed.

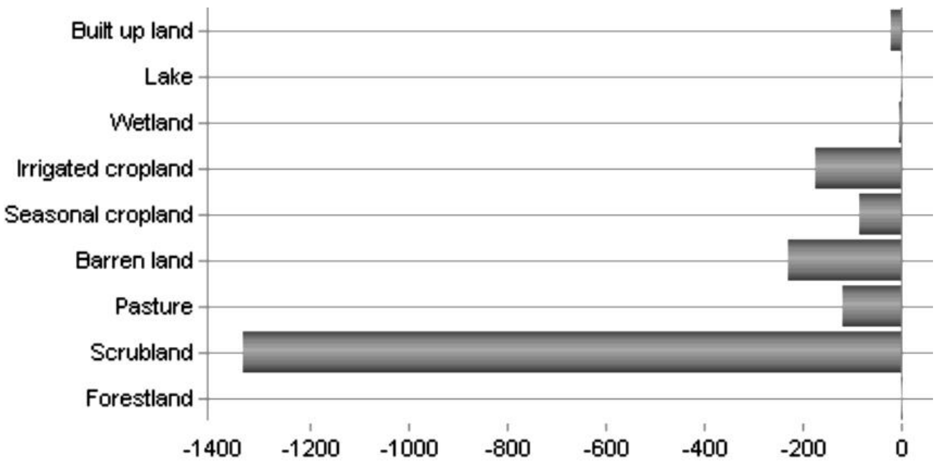

Figure 11. Contribution to the net change in Forest land (1988-1997) (ha), Huatanay watershed, Cusco, Peru.

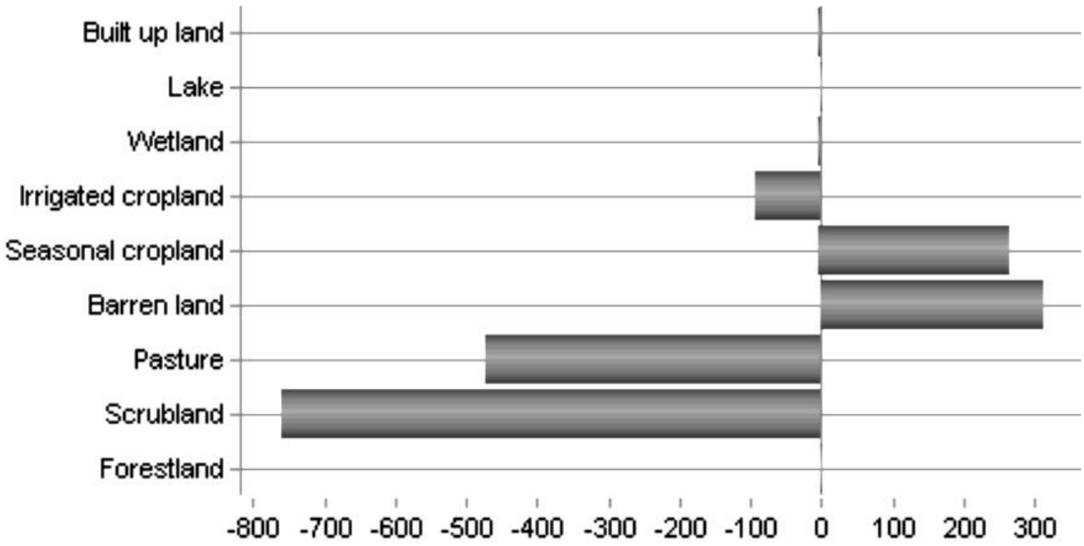

Figure 12. Contribution to the net change in Forest land (1997-2007) (ha), Huatanay watershed, Cusco, Peru.

Similarly, as seen in the figures of net change in Forest land in 1988-1997, Forest land class has lost area to Scrubland (1339 ha), to Barren land (231 ha) and to Irrigated cropland (174 ha). No gains have been detected on that period, which has caused deforestation. In 1997-2007 the Forest land has lost area mainly to Scrubland (761 ha) and to Pasture (474 ha) and has gained area mainly from Barren land (314 ha) and Seasonal cropland (269 ha). As it was described above, the Forestland class is dominated by the cultivated eucalyptus forest, which is under intensive economic exploitation, cutting, re-growing and reforestation.

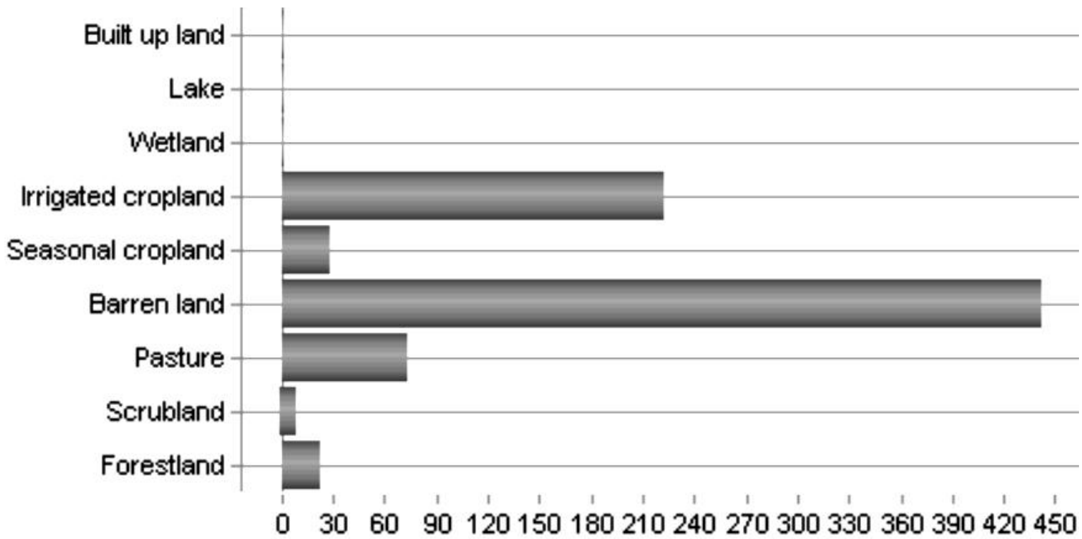

Figure 13. Contribution to the net change in Built up land (1988-1997) (ha), Huatanay watershed, Cusco, Peru.

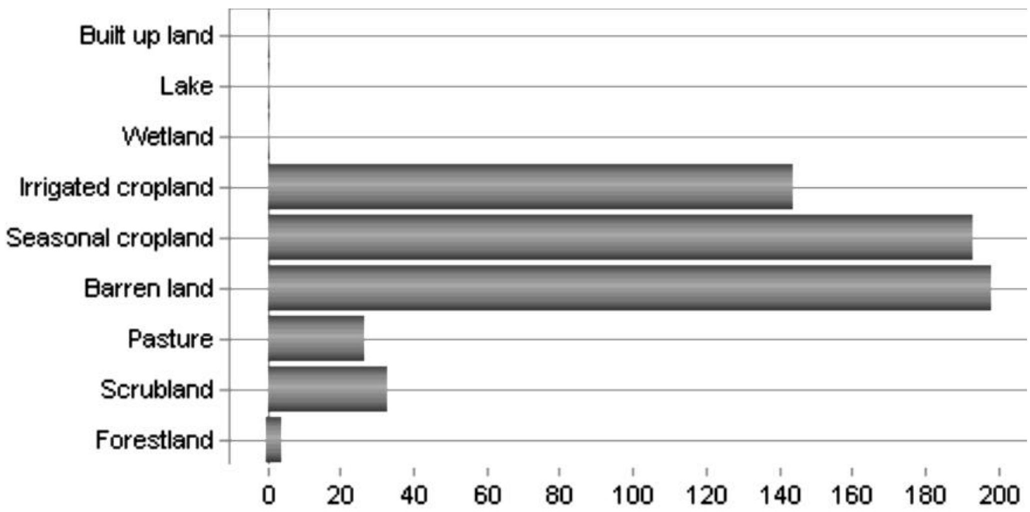

Figure 14. Contribution to the net change in Built up land (1997-2007) (ha), Huatanay watershed, Cusco, Peru.

The Built up land class in 1988-1997 has gained area mostly from Barren land (443 ha) and Irrigated cropland (223 ha), and in 1997-2007 mainly from Barren land (199 ha), Seasonal cropland (193 ha) and Irrigated cropland (144 ha).

Soil Erosion Modeled Results

The RUSLE factor was generated as follows:

Rainfall erosivity (R) factor was calculated using the data from the K'ayra weather station as a base station, and then regionalized to the surrounding stations using the relation (8). Table 4 lists the used stations. The water-balance climatograph (Figure 15) of K'ayra station shows that surface runoff happens in the rainy season (September to April) and in this period soil erosion might occur.

The geostatistical interpolation method Ordinary Kriging was used for generating the spatial rain erosivity factor for the study area, with a mean of 1.66, root mean square of 28.17, average standard error of 34.08 and standardized root mean square of 0.81. The result is given in Figure 16 (R Factor).

Table 4. Meteorological stations near the Huatanay watershed, Cusco, Peru, used for the estimation of RUSLE models' R factor. R factors are calculated using Equation (8).

N°	Station Name	Latitude	Longitude	Altitud (m)	Mean total annual precipiation (mm)	R factor (MJ mm) / (ha h)
1	Perayoc	13º31'12''	71º57'36''	3,365	796.28	133.84
2	K'ayra	13º33'24''	71º52'30''	3,219	665.40	97.75*
3	Cusco	13º32'17''	71º56'37''	3,399	717.20	111.45
4	Urubamba	13º18'37''	72º07'25''	2,863	433.63	46.20
5	Anta	13º28'05''	72º12'56''	3,440	736.43	116.73
6	Zurite	13º27'29''	72º15'35''	3,391	799.92	134.91
7	Urcos	13º41'12''	71º37'30''	3,169	607.60	83.38
8	Paruro	13º45'58''	71º50'49''	3,084	795.96	133.74
9	Paucartambo	13º56'45''	71º35'49''	3,042	553.20	70.76
10	Caycay	13º35'48''	71º42'01''	3,100	363.54	33.94

* Base station, value calculated by the RUSLE standard procedure

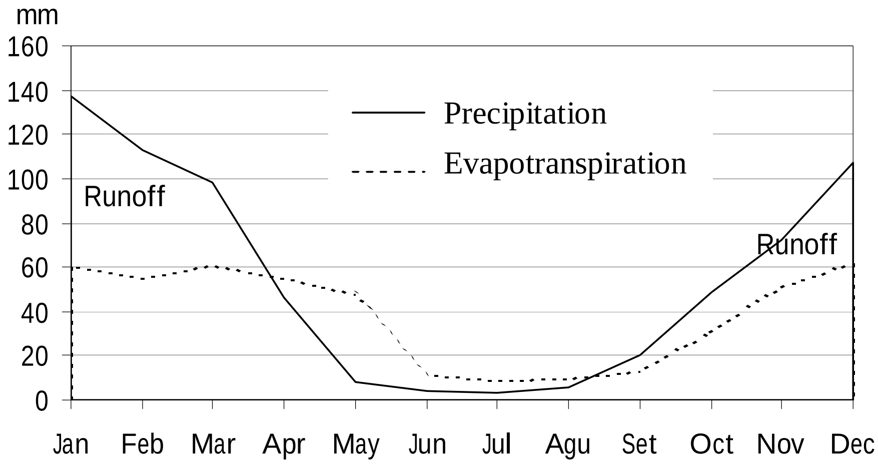

Figure 15. Water-balance climatograph of K'ayra weather station (recorded average 1965-2000, SENAMHI).

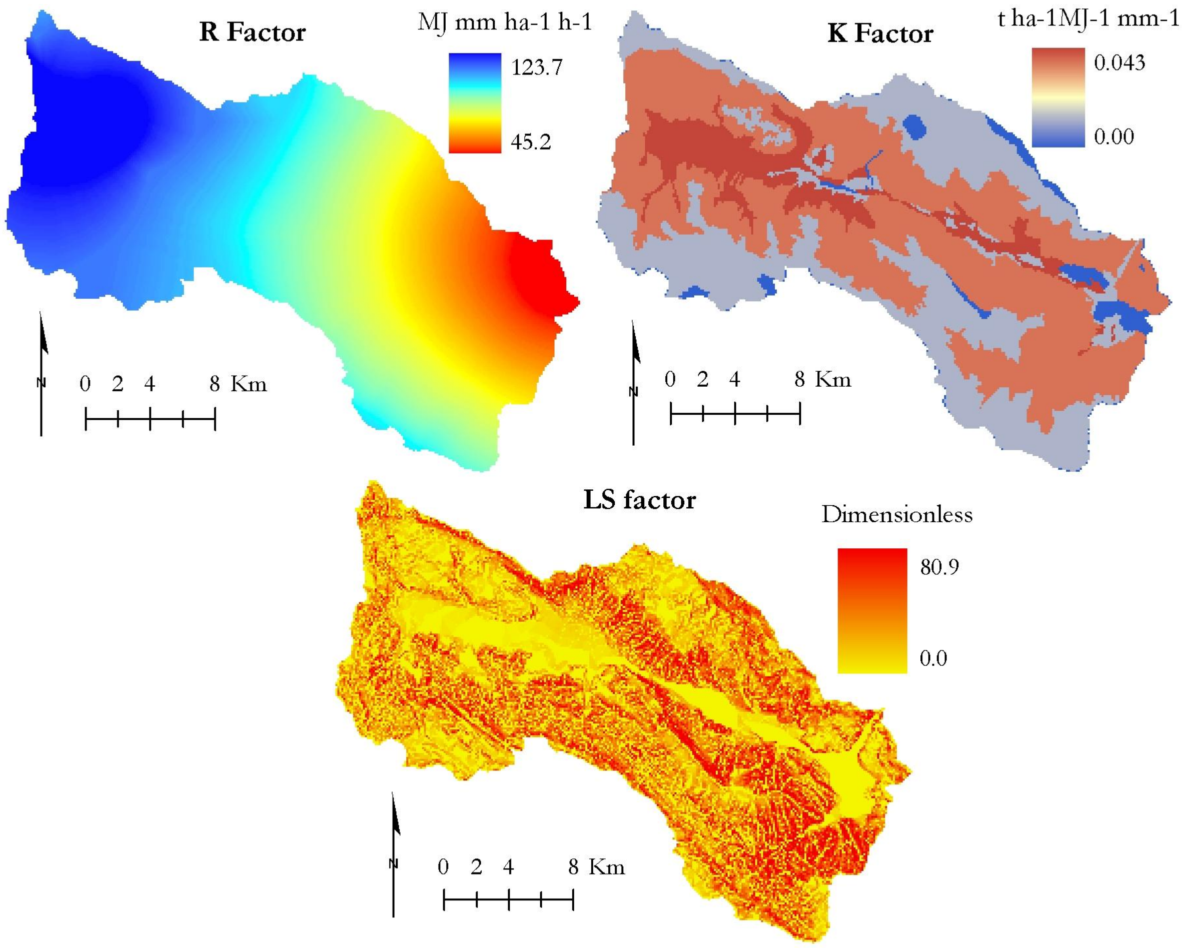

Figure 16. RUSLE soil erosion model's factor Maps calculated for Huatanay watershed, Cusco, Peru. Rainfall erosivity factor (R), Soil erodibility factor (K), Slope length and steepness (LS).

Soil erodibility (K) was calculated using previously characterized and generated soil maps (ONERN 1988, IMA 1994) and the formula to calculate the K factor (Table 7 in the appendix). The K factor was calculated for each soil type present at the watershed and joined to the attribute table in GIS. The result is given in Figure 16 (K factor).

Slope length and steepness (LS) factor was calculated using the Digital Elevation Models (DEM) constructed for the study area, based on topographic curve lines. Using Equation (9), it was generated automatically by the SATEEC algorithms. The result is given in Figure 16 (LS Factor).

For the cover management (C) factor information was collected from the field and from literary sources about dominant vegetation types in each LCLU class at the watershed, for example, characteristics of dominant forests, scrub and pasture type, crop types, cropping period and cropping systems, urban structure, etc. The RUSLE2 Software database was then used to calculate the C factor for each LCLU class. Table 5 shows the C factor values calculated by LCLU classes joined to the attribute table of the results of 1988, 1997, and 2007 Land Cover and Land Use maps.

Table 5. The C factors of Land Cover and Land Use (LCLU) Classes calculated for Huatanay watershed, Cusco, Peru.

No	Class	Area %	C factor	Podenrate C factor
1	Forestland	100	0.20	0.20
2	Scrubland	100	0.22	0.22
3	Pasture			0.24
	Good density	40	0.12	4.8
	Overgrazed	60	0.32	19.2
4	Barren land			0.64
	Rock	20	0.00	0
	Bared soil	40	1.00	40
	Scarse vegetation	30	0.60	18
	Other	7	0.80	5.6
5	Seasonal cropland			0.52
	Potato	60	0.56	33.72
	Barley	10	0.35	3.5
	others	30	0.50	15
6	Irrigated cropland			0.46
	Potato	16	0.562	8.99
	Mayz	36	0.448	16.13
	Wheat	8	0.26	2.08
	Barley for foraje	11	0.3	3.30
	Vegetables	18	0.55	9.90
	Bean	11	0.5	5.50
7	Wetland		0	0
8	Lake		0	0
9	Built up land			0.29
	Urban area	85	0.2	17
	Park	5	0.3	1.5
	Bared soil	10	1	10

Integrating the five RUSLE factor maps according to Equation (7) in a GIS system gives the results of soil loss which are presented in Figure 17. The annual average soil loss estimated in the Huatanay watershed was 319.5 ton/ha/year in 1988, 299.4 ton/ha/year in 1997 and 306.0 ton/ha/year in 2007. And the estimated total annual soil loss at the watershed was 2.83 million, 2.70 million, and 2.76 million t/yr in 1988, 1997, and 2007 respectively. Six categories of the soil loss according to its severity were classified and the differences in the proportion of the area were compared between the years (Table 6).

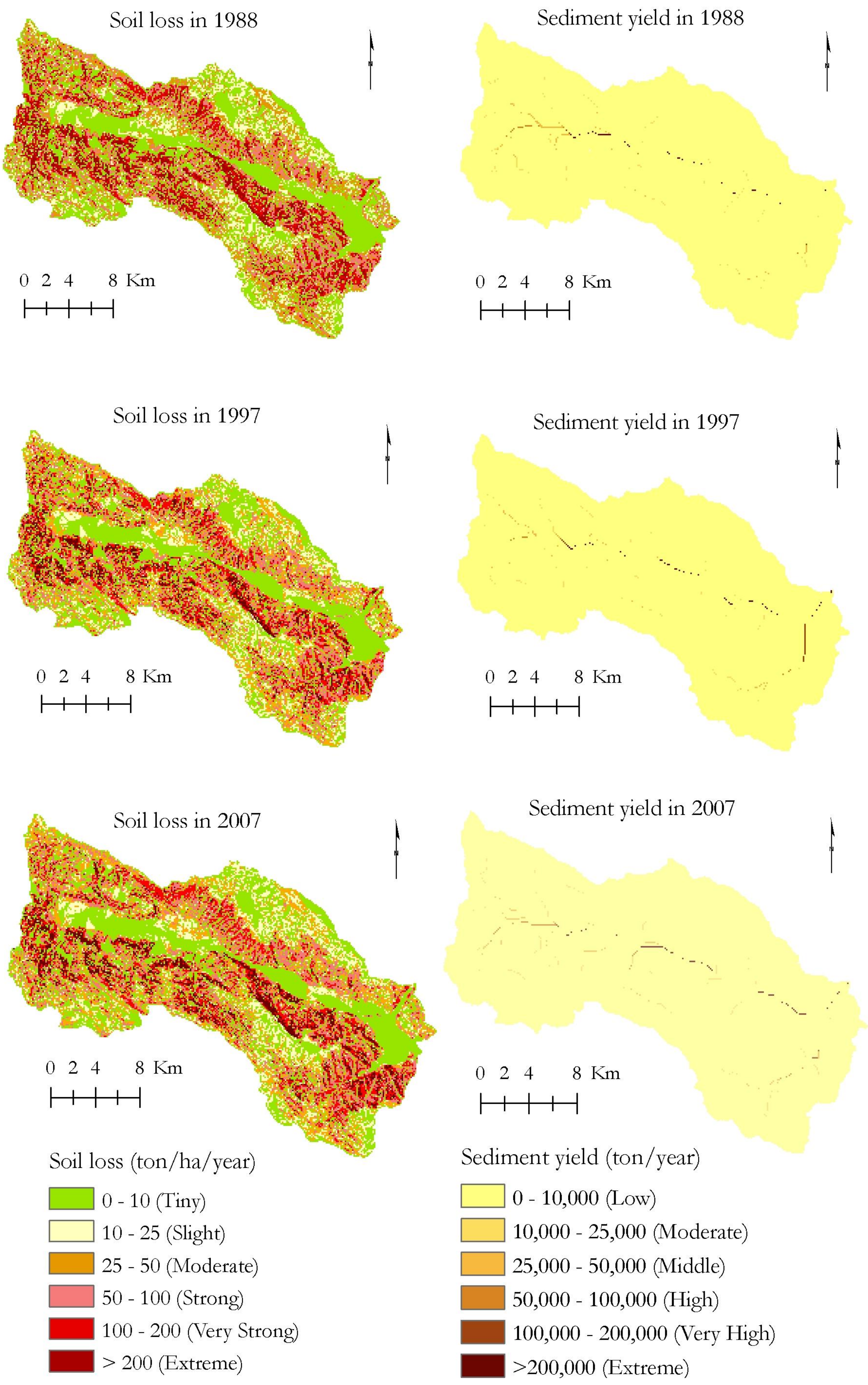

Figure 17. Modeled Soil Loss and Sediment Yield Maps for Huatanay Watershed, Cusco, Peru.

Table 6. Soil loss classes, classified from the modeled data, Huatanay watershed, Cusco, Peru.

Erosion Classes	1988 Ha	1988 %	1997 Ha	1997 %	2007 Ha	2007 %
Tiny (0-10 ton/ha/year)	17879.4	36.5	17799.9	36.3	17866.7	36.5
Slight (10- 25 ton/ha/year)	6347.6	13.0	5866.8	12.0	6127.7	12.5
Moderate (25-50 ton/ha/year)	7111.4	14.5	7448.0	15.2	7031.4	14.3
Strong (50-100 ton/ha/year)	8160.1	16.7	8659.4	17.7	8465.5	17.3
Very Strong (100-200 ton/ha/year)	5997.5	12.2	6347.3	13.0	6400.5	13.1
Extreme (>200 ton/ha/year)	3507.0	7.2	2881.6	5.9	3111.3	6.3
Total	49003	100	49003	100	49003	100

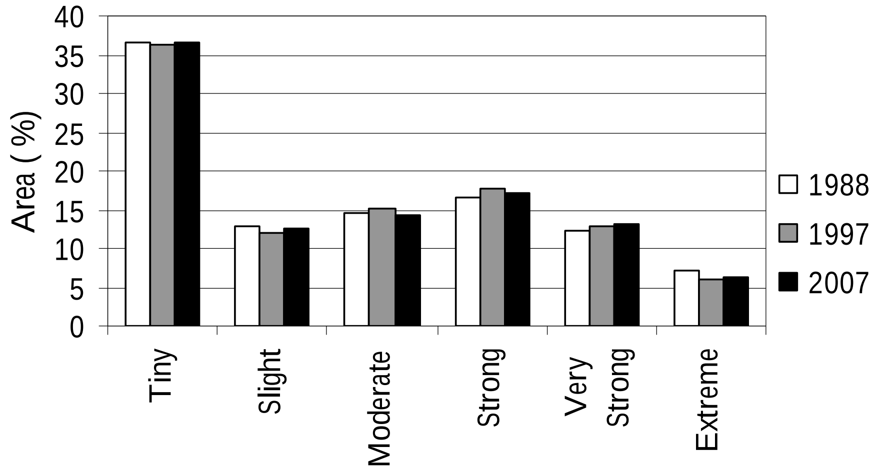

Figure 18. Areas (%) of the study area in Huatanay watershed (Cusco, Peru) belonging to each soil loss class compared between the years studied.

From Table 6 and Figure 18 it can be seen that no significant changes in the proportional area of the soil loss classes between the years can be observed. However, more than 50% of the watershed area in each year has soil loss from moderate to extreme, which means that the erosion problem is highly relevant in the Huatanay watershed. And high soil erosion is observed mainly in the middle part of the watershed (elevation from 3300 to 3700 m).

In order to analyze the amount of soil erosion in slopes of different degree, six classes of slope steepness were classified, and by using the zonal statistics (ArcGIS Spatial Analysis) the mean soil loss for each slope class and LCLU class was estimated (see Figures 19, 20 and 21).

Each LCLU class responded in a similar way to the slope steepness change with low soil loss in low slopes and high soil loss in high slopes. The slopes of 25-50%, 50-75%, and >75% had high soil loss in each class. The Barren land class has the highest value of soil loss in all slope classes, and the soil loss increased remarkably in the 25-50%, 50-75% and >75% slope classes, being 140.1, 239.8 and 290.6 ton/ha/year in 1988, 110.6, 210.8 and 250.0 ton/ha/year in 1997, and 130.5, 225.2 and 272.4 ton/ha/year in 2007. The second highest soil losses were in Seasonal croplands, where in the slope classes of 25-50%, 50-75% and >75% the soil losses were: 103.3, 171.9 and 213.0 ton/ha/year in 1988, 109.4, 183.2 and 228.3 ton/ha/year on 1997, 100.3, 168.1 and 203.9 ton/ha/year in 2007. These classes have large proportional area in the watershed in slopes >25% (see Figures 1, 2 and 3 in the appendix),

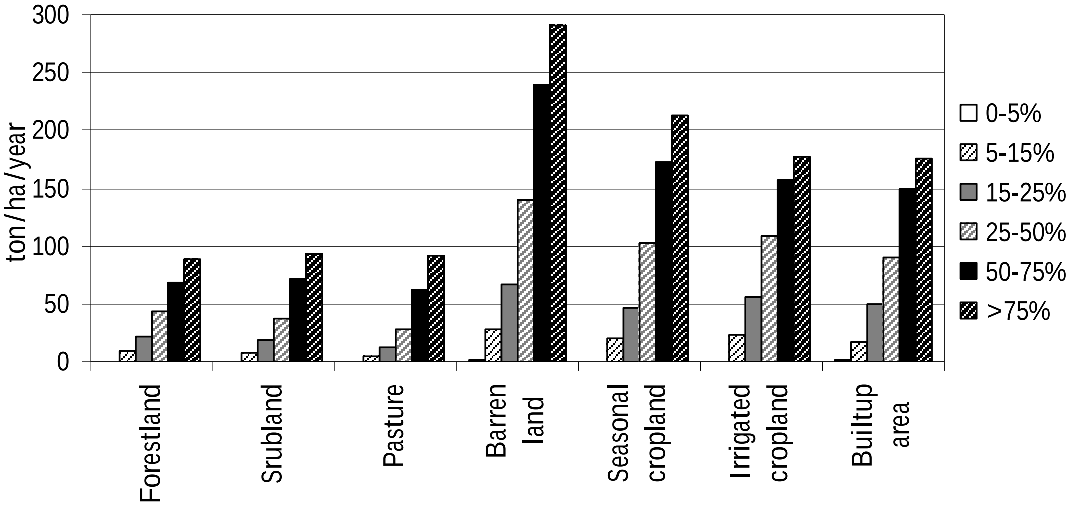

Figure 19. Soil loss by LCLU classes and slope classes in 1988. RUSLE modeled data for Huatanay watershed, Cusco, Peru.

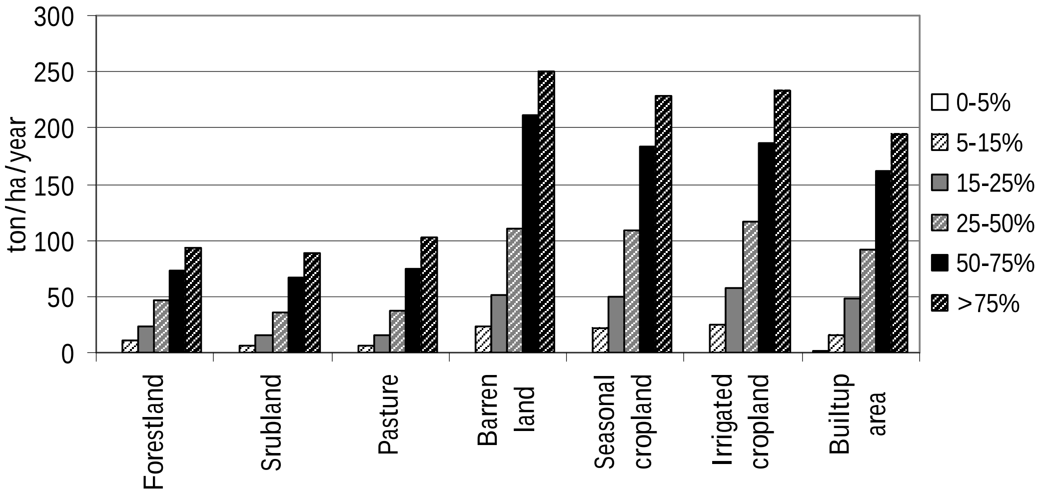

Figure 20. Soil loss by LCLU classes and slope slasses in 1997. RUSLE modeled data for Huatanay watershed, Cusco, Peru.

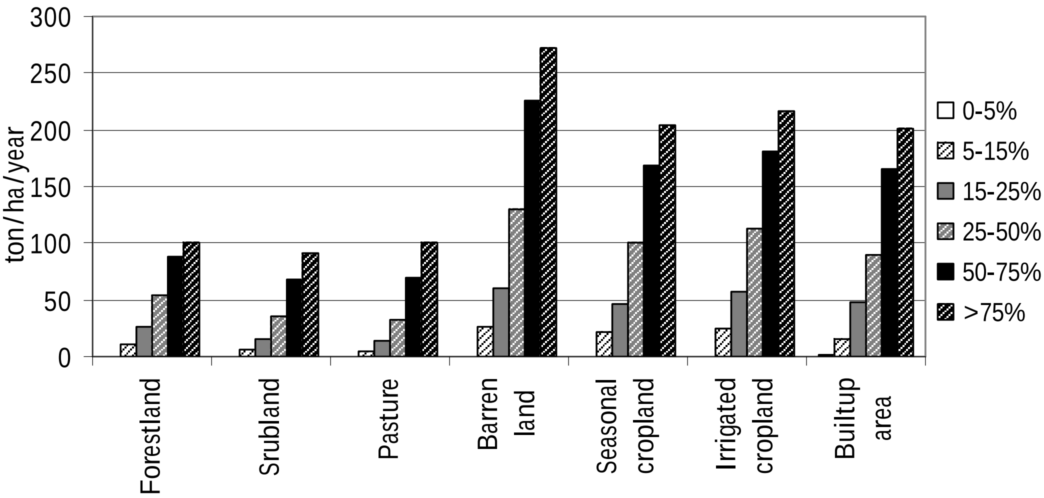

Figure 21. Soil Loss by LCLU classes and slope classes in 2007. RUSLE modeled data for Huatanay watershed, Cusco, Peru.

which means that in these classes the soil erosion problem is critical. The Irrigated cropland and Built up land classes also showed high soil losses in the slopes of 25-50%, 50-75% and >75%, but the area of these classes is small in slopes >25% (see Figures 1, 2 and 3 in the appendix).

In order to analyze statistically the Land cover and land use change impact on soil loss, mean soil loss in each slope class for each year was calculated using zonal statistics. The results are presented in Table 7 and Figure 22.

Table 7. Mean annual soil loss by slope classes, RUSLE modeled data, Huatanay watershed, Cusco, Peru.

Slope	Nro	1988		1997		2007	
Class	Pixels*	Mean	SEM	Mean	SEM	Mean	SEM
0 - 5 %	98446	0.63	0.01	0.6	0.01	0.6	0.01
5 - 15 %	64678	17.11	0.07	16.7	0.07	16.7	0.07
15 - 25 %	79142	36.26	0.14	35.5	0.13	34.9	0.13
25 - 50 %	191431	70.69	0.17	68.2	0.16	68.2	0.16
50 - 75 %	89591	120.64	0.37	112.7	0.33	118.7	0.34
> 75 %	21191	150.40	0.83	141.3	0.73	148.9	0.77

*Pixels (30*30m) count in the corresponding slope class.

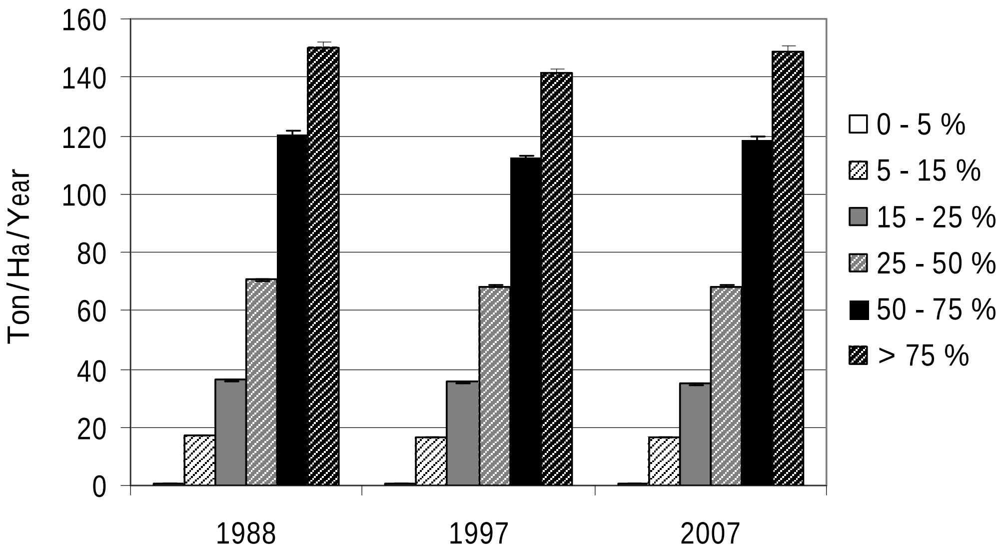

Figure 22. Mean annual soil loss by slope classes, RUSLE modeled data, Huatanay watershed, Cusco, Peru.

The differences in mean soil losses between years was significant (Fridman test p = 0.009). This gives a clear indication that changes in land cover and land use in Huatanay watershed affect significantly to the soil erosion rate.

The differences in soil loss rates between the low, middle and upper parts of the watershed (Figure 23A) were also analyzed and the result is showed in Figure 23B.

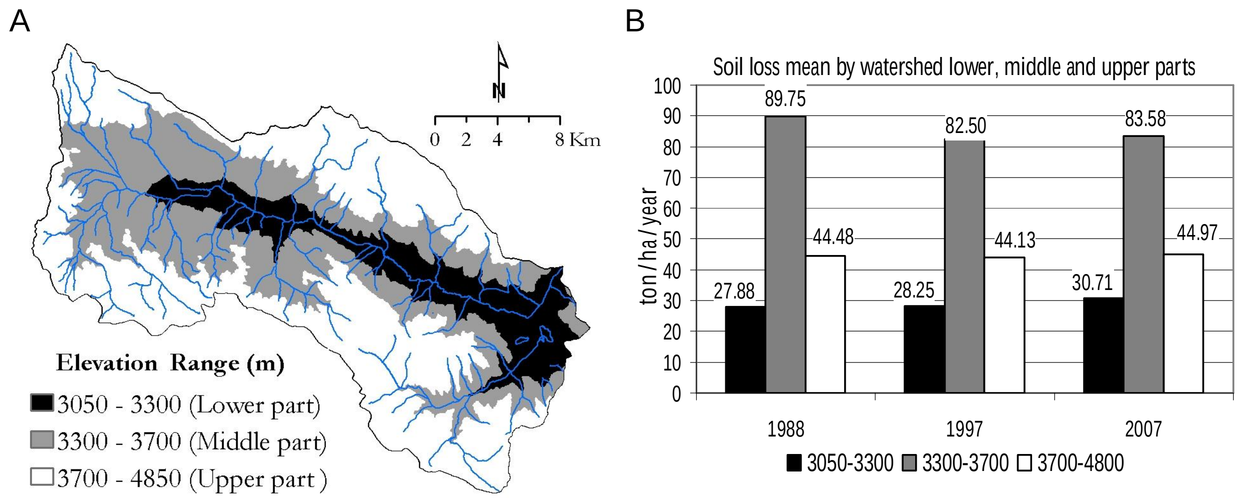

Figure 23. A) Watershed parts. B) Soil loss annual mean by watershed part, based on RUSLE modeled data, Huatanay watershed, Cusco, Peru.

High sediment production by soil erosion was observed occurring in the middle and upper parts of the watershed: 89.75 (1988), 82.50 (1997) and 83.50 (2007) ton/ha/year in the middle watershed part; 44.48 (1988), 44.13 (1997) and 44.97 (2007) ton/ha/year in the upper watershed part; and 27.88 (1988), 28.25 (1997) and 30.47 (2007) ton/ha/year in the lower watershed part. Both the middle and upper parts are located in slopes > 25%, but the middle parts are the steepest and probably for that reason the most sensitive to erosion.

A slight decrease from 1988 to 2007 in mean soil erosion in the middle parts was observed, where the major LCLU classes are the pasture, scrubland, barren land, and seasonal cropland, which are under strong human influence. However, the main LCLU changes in the middle part were the reduction of barren land and the increase of pasture area (Figures 1, 2 and 3 in the appendix). Consequently, this means an increase in vegetation cover and quality, which generally leads to a reduction in soil erosion and this can be recognized as watershed services for sediment control. As seen before, Seasonal croplands and Barren lands had high soil erosion in slopes > 25% (corresponding to the middle and upper parts of the watershed). When Pastures and Scrublands change to these erosion sensitive classes of Seasonal cropland and Barren land, a major impact to watershed services for soil erosion control in the Huatanay watershed is caused.

No big changes were observed in the upper parts of the watershed during the study period. In the lower parts the soil erosion has increased slightly which can be assumed to be a consequence of the decreasing of Forest land and Scrubland and the increasing of Built up areas in this part of the watershed.

Strategies to soil loss reduction in the Huatanay watershed can be undertaken through reforestation activities and encouraging conservation practices to achieve better crop land soil management in the watershed enhancing this watershed service particularly for the urban areas (infrastructure protection, water quality and flood risk reduction). Even though there have been initiated some reforestation programs by local institutions (i.e. Instituto de Manejo de Agua y Medio Ambiente, through the PROGAISH–II project, municipalities and NGO's), they have not been able to focus to the whole system of services. Most of these programs have involved only rural communities and activities have been temporal depending on external funding. Consequently, reduction of soil erosion and flooding risks has not yet been achieved.

Sediment yield Modeled Result

The Sediment delivery ratio obtained for the Huatanay watershed is 0.22 and the estimated Sediment Yield delivered into the watershed outlet was 617,620, 588,761 and 601,567 (ton/year) in 1988, 1997 and 2007, or 1260.37 ton/km^2/yr in 1988, 1201.48 ton/km^2/year in 1997, and 1227.61 ton/km^2/yr in 2007.

Very high values of sediment yield were registered in the downstream (> 100 000 ton/year), ranging from high to extreme (see Figure 17, sediment yield maps). The sediment yield values in downstream depend on erosion rates in upstream, at middle and high elevations. The urban growth in the floodplain, which is an important area for soil deposition, increases the sediment load into the river causing associated problems to river morphology and aquatic ecosystems.

Little information exists about sediment load in Huatanay watershed. Only some general diagnoses about river contamination, IMA (1994), IMA (1997) and GPA (2004) containing some descriptions of the river water properties and simple instantaneous suspended sediment values, have been measured, but it does not represent an average concentration per day nor the monthly average. Due to the lack of a long term recorded data about river sediment load, it is difficult to validate the result of the sediment yield modelled here.

6 Conclusion

This study aimed to generate, quantify and analyze the land cover and land use (LCLU) information and LCLU change in the period of 1988 – 2007 in Huatanay watershed of Cusco region in Tropical Andes of Peru, using Landsat series satellite image data and other literary information. It also aimed to model the impact of LCLU change on the watershed erosion and sediment yield regulation services and to identify the upstream and downstream relationship on sediment control.

Multitemporal land cover and land use maps were generated for the study area by processing the Landsat TM images of the years 1998, 1997 and 2007. The statistical comparison of the classified LCLU maps of 1988, 1997 and 2007 through a cross-tabulation analysis gave an overall kappa index of: 0.41 for 1997-1988 and 0.40 for 2007-1997, meaning significant changes between the classes in studied periods. The land use change assessment through evaluating the area gains and losses and net change in each LCLU classes showed a high dynamic state of the Huatanay watershed landscape. In most of the LCLU classes area losses and gains of more than 50% were observed between the studied years. Built up land class differed from the other LCLU classes having only gains but no losses. It was perceived that most of the changes in the LCLU classes were caused by human action.

The soil erosion model allowed the identifying of the critical areas of soil loss in the watershed and the impact of the LCLU change on soil loss rate. The estimated annual average soil loss in the Huatanay watershed differed between the years being 319.5, 299.4, and 306.0 ton/ha/year in 1988, 1997 and 2007 respectively (Friedman test, $p = 0.009$). This general decreasing trend was assumed to be caused by changes in the LCLU. However, more than 50% of the watershed area had soil loss from moderate to extreme in each studied year, which means that the erosion problem is highly relevant in the Huatanay watershed. The soil erosion varied strongly with slope steepness in each LCLU class, the highest soil losses occurring in slopes > 25%, mainly located on the middle and upper parts of the watershed. Barren land and Seasonal cropland have probably the most significant impact on soil loss in the level of the whole watershed because of their high soil loss rates and of their large area proportion residing in the steep slopes of >25 %.

The estimated sediment yield in the watershed was 1260.37 ton/km^2/yr in 1988, 1201.48 ton/km^2/year in 1997, and 1227.61 ton/km^2/yr in 2007. The highest values of sediment yield were registered in the downstream areas indicating a high sedimentation process in this area. This is a serious problem in downstream areas and it is getting worse by urban growth in flood plains, which are important areas for soil deposition. When soil deposition areas are reduced, the sediment yield to the river is increased. Even though the result of the sediment yield model was not validated because of the lack of sediment load data from the Huatanay river, it seemed to work identifying areas with high risks of sediment accumulation.

There was a clear quantitative sediment production and accumulation relationship between upper and lower parts of Huatanay watershed in the studied years. High sediment production by soil erosion was occurring in the middle and upper parts of the watershed and high sediment accumulation in the downstream.

7 Recommendation

- The use of remote sensing based GIS analyses in mountain areas has still many challenges to overcome. The accuracy of image classification methods could be tested more rigorously using ancillary and ground data.

- The land cover and land use change could be studied with increased time resolution (like an interval of 5 years) and modeled linking more potential explanatory variables. Since all the classes are not explained by the same set of variables, a suitable set of explanatory variable should be looked for each LCLU class.

- A long term sediment load monitoring can be undertaken in the Huatanay watershed to evaluate trends in sediment yield in relation to land management, which can provided a daily, monthly and yearly sediment load variation. This kind of data can support simulation model calibration and validation, and to develop indicators for watershed service conditions.

- As the Huatanay watershed is an important area of urban, tourism and economic development, an integrated long term watershed monitoring could be undertaken, and a sustainable watershed management plan based on a watershed service reward system could be developed.

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Appendix

Table 1. Transformed divergence evaluation for 1988 Image without Shade

Signature Name		1	2	3	4	5	6	7	8
Forestland	1	0	1993.8	1999.93	1867.94	2000	1999.99	1999.98	1999.82
Irrigated cropland	2	1993.8	0	1999.33	1895.77	2000	1987.72	1971.66	1999.57
Pasture	3	1999.93	1999.33	0	1990.45	1740.39	1864.18	1995.51	2000
Scrubland	4	1867.94	1895.77	1990.45	0	1999.99	1987.25	1998.05	1993.87
Seasonal cropland	5	2000	2000	1740.39	1999.99	0	1975.86	1996.39	2000
Barren land	6	1999.99	1987.72	1864.18	1987.25	1975.86	0	1730.59	2000
Built up land	7	1999.98	1971.66	1995.51	1998.05	1996.39	1730.59	0	2000
Wetland	8	1999.82	1999.57	2000	1993.87	2000	2000	2000	0

Table 2. Transformed divergence evaluation for 1988 Image under Shade

Signature Name		1	2	3	4
Forestland	1	0	2000	2000	1939.94
Lake	2	2000	0	2000	2000
Pasture	3	2000	2000	0	1959.7
Scrubland	4	1939.94	2000	1959.7	0

Table 3. Transformed divergence evaluation for 1997 Image without Shade

Signature Name		1	2	3	4	5	6	7	8
Scrubland	1	0	2000	1960.87	1998.11	1832.18	1999.96	1860.38	1743.05
Seasonal cropland	2	2000	0	1977.46	1720.73	2000	1959.9	1999.75	2000
Irrigated cropland	3	1960.87	1977.46	0	1828.95	1872.11	1955.34	1773.2	1997.31
Pasture	4	1998.11	1720.73	1828.95	0	1999.28	1994.9	1834.66	1999.63
Forestland	5	1832.18	2000	1872.11	1999.28	0	1999.96	1959.31	1933.07
Built up land	6	1999.96	1959.9	1955.34	1994.9	1999.96	0	1995.29	2000
Barren land	7	1860.38	1999.75	1773.2	1834.66	1959.31	1995.29	0	1990.91
Wetland	8	1743.05	2000	1997.31	1999.63	1933.07	2000	1990.91	0

Table 4. Transformed divergence evaluation for 1997 Image under Shade

Signature Name		1	2	3	4
Cloud	1	0	2000	2000	2000
Forestland	2	2000	0	2000	1768.12
Lake	3	2000	2000	0	1999.84
Scrubland	4	2000	1768.12	1999.84	0

Table 5. Transformed divergence evaluation for 2007 Image without Shade

Signature Name		1	2	3	4	5	6	7	8
Forestland	1	0	1958.56	1999.94	1993.08	2000	2000	1999.94	1995.39
Irrigated cropland	2	1958.56	0	2000	2000	1999.94	2000	1999.97	1999.84
Pasture	3	1999.94	2000	0	1937.23	1908.12	1912.26	1999.86	1990.69
Scrubland	4	1993.08	2000	1937.23	0	2000	1997.95	1999.99	1989.33
Seasonal cropland	5	2000	1999.94	1908.12	2000	0	1907.3	1967.78	1999.89
Barren land	6	2000	2000	1912.26	1997.95	1907.3	0	1926.93	1999.5
Built up land	7	1999.94	1999.97	1999.86	1999.99	1967.78	1926.93	0	1999.87
Wetland	8	1995.39	1999.84	1990.69	1989.33	1999.89	1999.5	1999.87	0

Table 6. Transformed divergence evaluation for 2007 Image under Shade

Signature Name		1	2	3	4
Forestland	1	0	2000	1999.72	1949.79
Lake	2	2000	0	2000	2000
Pasture	3	1999.72	2000	0	1942.23
Scrubland	4	1949.79	2000	1942.23	0

Table 7. Cross-tabulation of LCLU 1988 (columns) against LCLU 1997 (rows)

	1	2	3	4	5	6	7	8	9	Total
1	34064	10973	878	2216	2619	1122	1	12	28	51913
2	25847	56188	9941	5542	3854	826	11	119	85	102413
3	2226	7434	58111	23456	23948	1452	1	0	232	116860
4	4787	12465	25942	39476	12210	4758	156	10	668	100472
5	3564	7936	12054	32456	51449	1639	86	0	558	109742
6	3051	1781	37	4447	2390	17309	132	8	471	29626
7	35	37	0	188	14	185	2739	103	0	3301
8	4	1	0	3	17	1	21	545	0	592
9	280	192	1044	5587	872	2951	1	0	18632	29559
Total	73858	97007	108007	113371	97373	30243	3148	797	20674	544478

Forestland (19, Scrubland (2), Pasture (3), Barren land (4), Seasonal cropland (5), Irrigated cropland (6), Wetland (7), Lake (8), and Built up land (9).

Chi Square : 1633899.12500
Df : 64
P-Level : 0.0000
Cramer's V : 0.6125

Table 8. Cross-tabulation of LCLU 1997 (columns) against LCLU 2007 (rows)

	1	2	3	4	5	6	7	8	9	Total
1	19917	8820	2237	4582	6214	1716	12	0	77	43575
2	17281	57653	6612	8947	3849	588	109	13	63	95115
3	7502	21201	58742	30563	12328	215	12	0	440	131003
4	1093	4386	19577	32720	26270	4564	173	0	1603	90386
5	3222	7987	27497	14488	56067	2348	22	7	458	112096
6	2748	1850	1461	5205	2383	17753	65	0	696	32161
7	5	23	0	156	26	142	2825	22	3	3202
8	18	62	0	2	1	0	80	550	0	713
9	127	431	734	3809	2604	2300	3	0	26219	36227
Total	51913	102413	116860	100472	109742	29626	3301	592	29559	544478

Forestland (19, Scrubland (2), Pasture (3), Barren land (4), Seasonal cropland (5), Irrigated cropland (6), Wetland (7), Lake (8), and Built up land (9).

Chi Square : 1646743.12500
Df : 64
P-Level : 0.0000
Cramer's V : 0.6149

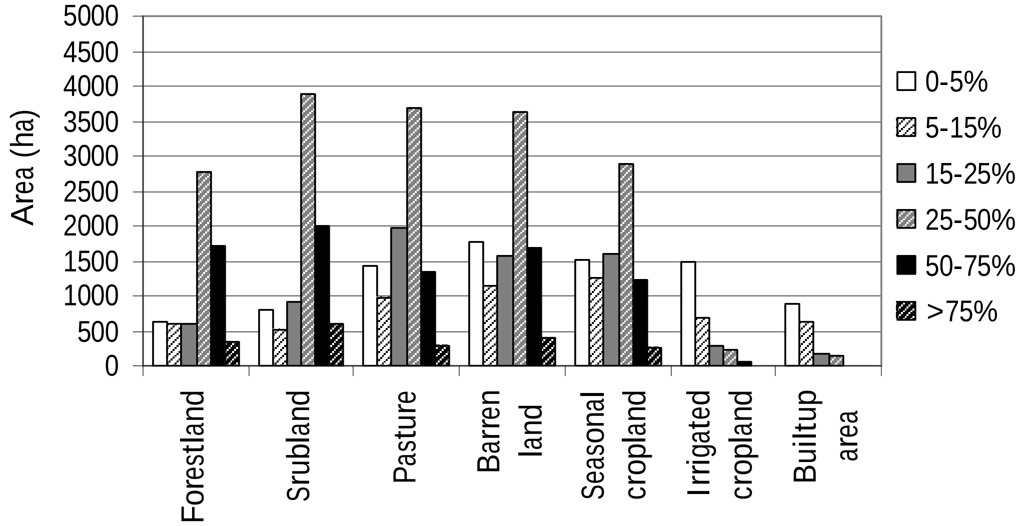

Figure 1. 1988 LCLU Classes by Slope Classes

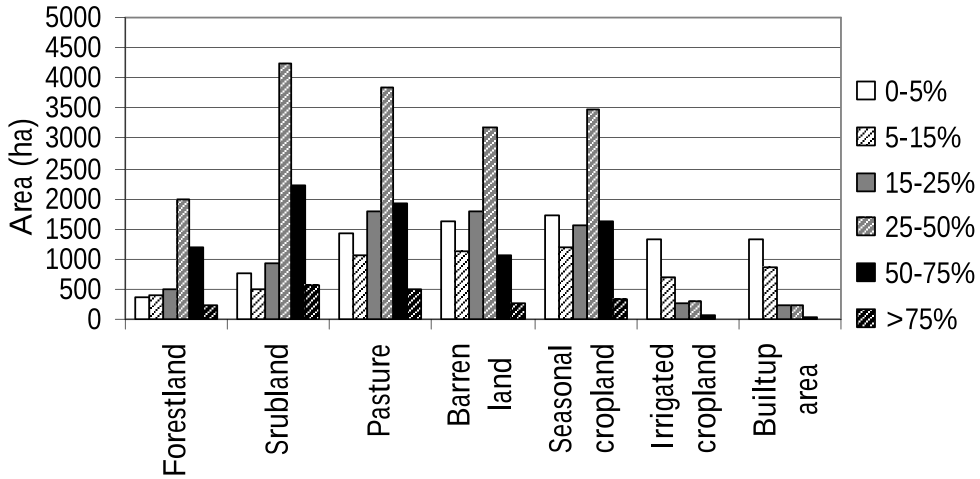

Figure 2. 1997 LCLU Classes by Slope Classes

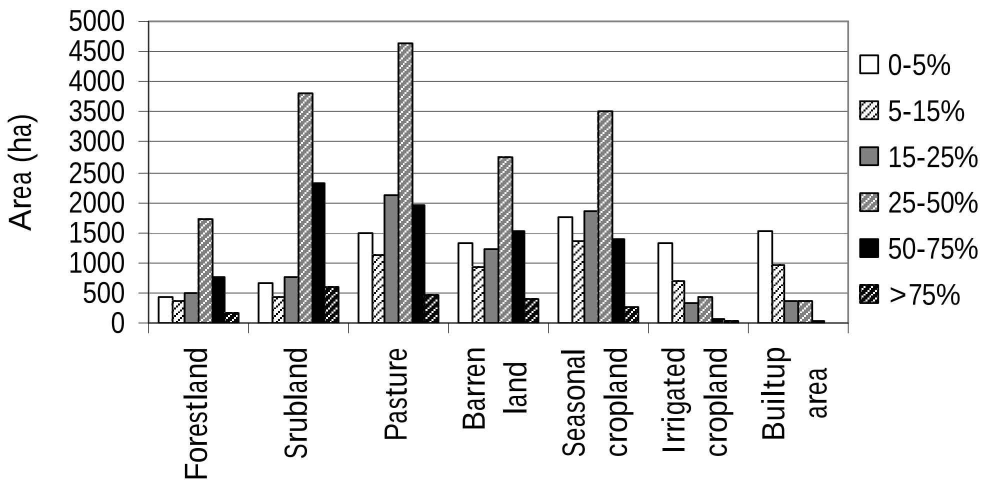

Figure 3. 2007 LCLU Classes by Slope Classes

Table 9. RUSLE Factor Estimation Equation

Operating equation	Parameter definitions
R: Erosivity factor (MJ mm)/(ha h)	
$R = \sum R_m \ / \ M$	R_m: Erosivity for an individual storm M: Number of storms
$R_m = EI_{30}$	E: total storm energy (MJ/ha) I_{30}: Maximum 30-min intensity of individual storm (mm/h)
$E = e \Delta V$	e: Unit energy (MJ/(ha mm)) ΔV: Rainfall amount (mm)
$e = 0.29 [1 - 0.72 \exp (- 0.082 \, i)]$	*i*: Rainfall intensity (mm/h)
K: Soil erodibility factor (t/ha)/(MJ mm)	
$K = (k_t k_o + k_s + k_p) \ / \ 100$	K: Soil erodibility factor (t/ha)/(MJ mm) K_t: Soil texture subfactor K_o: Soil organic matter subfactor K_s: Soil structure subfactor K_p: Ssoil profile permeability subfactor
$K_{tb} = 2.1 [(P_{sl} + P_{vfs}) (100 – P_{cl})]^{1.14} \ / \ 10000$	P_{sl} : percentage of silt P_{vfs} : percentage of very fine sand
$K_{t68} = 2.1 [68 (100 - P_{cl})]^{1.14} \ / \ 1000$	P_{cl} : percentage of clay
$K_t = K_{tb}$ for $P_{sl} + P_{vfs} \leq 68$ %	K_{tb} : base soil texture subfactor
$K_t = K_{tb} – [0.67 (K_{tb} - K_{t68})^{0.82}]$ for $P_{sl} + P_{vfs} > 68\%$	K_{t68}: soil texture subfactor corresponding to 68%
$P_{vfs} = (0.74 – 0.62 P_{sd} \ / \ 100) P_{sd}$	P_{sd}: percentage of sand
$K_o = (12 - O_m)$	O_m : percentage of inherent soil organic matter
$K_s = 3.25 (S_s – 2)$	S_s : Soil structure class (1 – very fine granular, 2 – fine granular, 3 – medium or coarse granular and 4 – blocky, platy or massive)
$K_p = 2.5 (P_r – 3)$	P_r : soil profile permeability rating (1 – rapid , 2 – moderate rapid, 3 – moderate, 4 – slow to moderate, 5 – slow and 6 – very Slow)
L: Slope length factor	
$L = (m + 1) (x / \lambda_u)^m$	L : Slope length factor x : Distance from the origin of over land flow path (m) λ_u : Length of unit plot (22.17 m) m : Slope length exponent
$m = \beta / (1- \beta)$	k_r / k_i : rill to interill soil erodibility ratio
$\beta = (k_r / k_i) (C_{pr} / C_{pi}) [\exp (- b_r f_{ge}) / \exp (- 0.025 f_{ge})] \{ (\sin\theta / 0.896) / [3 (\sin \theta)^{0.8} + 0.56] \}$	C_{pr}/C_{pi} : rill to interill prior land use soil erodibility ratio $[\exp(-b_r f_{ge})/\exp(–0.025 f_{ge})]$: rill erosion surface cover effect to interill erosion surface cover effect ratio,
$K_r / k_i = (P_{sd} / 100) (1-\exp(-0{:}05P_{sd})) + 2.7 (P_{sl} / 100)^{2.5} (1- \exp (-0.05P_{sl})) + 0.35 (P_{cl} / 100) (1 - \exp (0.05P_{cl}))$	b_r : coefficient for conformance of ground cover that describes the relative effectiveness of the ground cover for reducing erosion. The value ranges from 0.05–0.06. $\{(\sin\theta/0.896)/[3(\sin\theta)^{0.8}+0.56]\}$: slope effect for rill erosion to slope effect for interill erosion
$C_{pr} / C_{pi} = 0.45 + 1.55 (S_c S_b)^2$	S_c : soil consolidation subfactor S_b : soil biomass subfactor
$f_{ge} = f_{gn} (0.4 + 0.6 \delta)$, where $\delta = (b_r – 0.05) / 0.01$	f_{ge} : effective ground cover. f_{gn} : net ground cover, portion of soil surface covered
S: Slope steepness factor	
$S = 10.8 \sin \theta + 0.03$, $S_p < 9\%$	S_p : Steepness of the overland flow path (%)
$S = 1608 \sin \theta – 0.5$ $S_p > 9\%$	
$\theta = \tan^{-1} (S_p / 100)$	

C: Cover management factor

$C = C_c * G_c * S_r * S_b * r_h * S_c * S_m$

C_c : canopy subfactor
G_c : ground cover subfactor
S_r : soil surface roughness subfactor
S_b : soil biomass subfactor
r_h : ridge height subfactor
S_c : soil consolidation subfactor
S_m : antecedent soil moisture subfactor

$C_c = 1- f_{ec} \exp (0.1h_f)$
$f_{ec} = f_c (1 – f_{gn})$
$h_f = h_b + a_s a_g (h_t – h_b)$

a_g: coefficient related to height within the canopy where vegetative surface area is concentrated, used to compute effective fall height
a_s coefficient that is a function of canopy shape used to compute effective fall height
f_c: canopy cover
f_{ec}: effective canopy cover
f_{gn} : net ground cover, portion of soil surface covered
h_b : height to bottom of canopy cover (inches)
h_f : effective fall height
h_t : height to top of canopy cover (inches)
f_{gn} : 100-bare ground

$g_c = \exp (- b f_{gn} (0.24 / R_a) ^{0.08})$

b : Coefficient (percent-1) that is a function of ground cover type and the ratio of rill to interill erosion
R_a : initial roughness value

$Sr = (- 0.66 (R_a – 0.24))$

$Sb = 0.951 \exp (- 0.0026 B_{rt} - 0{:}0006 B_{rs} / S_c ^{0.5})$; $Sb \leq 0.9035$
$Sb = \exp (- 1.9785 (0.0026 B_{rt} + 0.006 B_{rs} / Sc ^{0.5})$; $Sb > 0{:}9035$
$r_{h6} = 0.9 (1+ 0.0582 H ^{1.84})$; $H > 3$ inches
$r_{h6} = 2.136(1 - \exp(-0{:}484 H))- 0.336$; $H > 3$ inches
$r_h = r_{h6}$; $Sp < 6\%$
$r_h = 1+(r_{h6} – 1) \exp (a_h (Sp- 0.05989))$; $Sp \geq 6\%$

B_{rt} : buried root mass density (gms / cm^3)
B_{rs} : buried residue mass density (gms / cm^3)
H : ridge height (inches)
a_h : coefficient used to compute ridge height subfactor values

$a_h =16.02 – 0.927H$ for $H \leq 10$ inches
$a_h = 6{:}75$ for $H > 10$ inches
$S_c = 0.45 + \exp (-3.314 (0.1804 + (t_d / t_c) ^{1.439}))$
t_c 20 ; $P_a < 10$
t_c 26.5 – 0.65 + 0.5; $10 \leq P_a \leq 30$
t_c 7 ; $30 < P_a$

P_a: Average precipitation (mm)
t_c : time to soil consolidation (days)
t_d : time since the last mechanical soil disturbance (days)

P: Supporting practices factor

$P = a (S_m - S_c) ^4 + P_{bm}$; $S_c < S_m$
$P = a (S_c - S_m) ^{1.5} + P_{bm}$; $S_m \leq S_c \leq S_{be}$
$P = 1$; $S_{be} < S_c$

$a = (1 - P_{bm}) / S_m{}^4$
$P_b = 1$ at $S_c = 0$
$P_b = P_m$ at $S_c = S_m$
$P_b = 1$ at $S_c = S_{be}$

S_m: land steepness
S_c: scaled land steepness (sine of the slope angle)
a: coefficient used to compute values for base contouring subfactor values
S_{be}: steepness that the contouring subfactor reaches 1
h_e: effective ridge height (maximum value is 8 inches)
P_b: base contouring subfactor
P_m: minimum base contouring subfactor

$P_{bm} = 0.05 + 0.95 \exp (0.5512 h_e)$ if $h_e > 8$, if $h_e = 8$ inches
$S_m = 4 (1 - \exp (- 0.1903 h_e)) + 4$ if he > 8; if $h_e = 8$ inches
$S_{be} = \sin (\tan ^{-1}(9 + 53.09 h_e / 8 * 100))$ if $h_e > 8$; $h_e = 8$ inches